Hardware Accelerator Design with Supervised Machine Learning for Solar Particle Event Prediction

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***Abstract*—The intensity of cosmic radiation can differ over five orders of magnitude within a few hours or days during Solar Particle Events (SPEs), thus increasing the probability of Single-Event Upsets (SEUs) in space applications for several orders of magnitude. Therefore, it is vital to employ the early detection of the SEU rate changes in order to ensure timely activation of the radiation hardening measures. In this paper, a hardware accelerator for forecasting the SPEs by the prediction of in-flight SEU variation is proposed. An embedded on-chip SRAM is used as the real-time particle detector. The dedicated hardware accelerator implements a supervised machine learning model to forecast the SRAM SEUs one hour in advance with fine-grained hourly tracking of SEU variations during SPEs as well as under normal conditions. The whole design is intended for a highly dependable and self-adaptive multiprocessing system employed in space applications. Therefore, the target system can drive the appropriate radiation hardening mechanisms before the onset of high radiation levels.**

Keywords*— *solar particle event, machine learning, single event upset, hardware accelerator

I. Introduction

As technology scales into the deep nanometer range, the space community faces more and more reliability challenges. The radiation-induced effects, especially the Single Event Upsets (SEUs), are one of the major reliability concerns in the design of integrated circuits for space applications [1]. The SEU (also commonly known as the soft error) is a transient bit flip in memory elements (flip-flops, latches and SRAM cells) caused by an energetic particle (e.g. heavy-ions and protons) that passes through the sensitive regions within an off-state transistor. Due to SEUs, the temporary malfunction or complete failure of electronic systems may occur. Therefore, the effective mitigation of SEUs in electronic systems for space applications is mandatory.

The Solar Particle Event (SPE) phenomenon is one of the main causes of SEUs in space applications [2]. During these events, high fluxes of energetic particles are emitted into space and this condition can last from several hours up to several days [3, 4]. These energetic particles can induce SEUs either by direct ionization (heavy-ion-induced) or by ionization resulting from nuclear reactions (proton-induced). As the particle flux directly determines the Soft Error Rate (SER) of an electronic system, it is vital to detect the variation in particle flux and consequently activate the suitable radiation hardening measures to protect the sensitive electronic systems. A typical protection solution is the self-adaptive multi-core processing system, in which the cores can be coupled into various rad-hard modes (e.g. Triple Modular Redundancy) during the high radiation fluxes. Conversely, when the particle flux is low, the high performance modes (all cores execute different tasks) or low power mode (some cores are switched off) can be employed [5].

The detection of SPEs is achieved with particle detectors which allow for measuring the particle flux in terms of the soft errors induced in the sensing elements [6]. However, in order to achieve efficient SEU mitigation and thus maintain the functionality of the system, it is important to enable the real-time prediction of the flux variations, i.e. to predict when an SPE will occur. In such a way, the radiation hardening mechanisms can be activated before the onset of an SPE and then switched off when the SPE ends. This enables to utilize efficiently the system resources according to the application requirements. To facilitate the SPE prediction in real-time, various machine learning algorithms can be applied to train the system for predicting the SER variations from the real-time SER measurements.

A number of space applications have employed machine learning models for SPE prediction. This was mainly done for research purposes, evaluation of space weather conditions and planning the space missions [7-9]. However, to the best of our knowledge, there is no much of publicly available work on the use of machine learning algorithms for predicting the SPEs from in-flight SER data, in order to drive the self-adaptive fault tolerance in space-borne systems. To minimize the on-board computational effort, the supervised (off-line trained) machine learning approach is the preferred choice for self-adaptive space applications. In our previous work [10], five machine learning models have been investigated for the SER prediction one hour in advance, as well as for the fine-grained hourly tracking of SER variations during SPEs. It was demonstrated that the recurrent neural network (RNN) with long short-term memory (LSTM) model and the linear regression model provide the best accuracy in SER prediction. However, the corresponding hardware implementation has not been addressed.

Considering the high hardware complexity and cost for the LSTM network [11], this machine learning model is not suitable for implementation in a low-cost embedded design. In that regard, in this work we have chosen the linear regression machine learning model, which shows an acceptable prediction accuracy with a much simpler implementation than the LSTM model. Moreover, a corresponding low-cost hardware accelerator design for the prediction of the in-flight SEU rate one hour in advance during SPEs and under normal conditions is customized. This work uses an embedded on-chip SRAM as a real-time particle detector and the linear regression supervised machine learning model implemented on a hardware accelerator to forecast the SEU rate of SRAM. In this way, the

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cost and area/power overheads of the proposed design can be negligible compared to the host SRAM. The importance of such design is the fact that the ability to predict the increased radiation levels minimizes the risk that the target system will be exposed to adverse conditions without being sufficiently protected.

The rest of the paper is organized as follows. Section II gives a brief description of the proposed system. Section III explains the data analysis and supervised machine learning models training process. The architecture of the proposed hardware accelerator is described in Section IV. Analysis of results is given in section V. The conclusion and the main directions for future work are outlined in section VI.

II. System Design

The block diagram of the system for the prediction of in-flight SRAM SEUs and SPEs is illustrated in Fig. 1. The basic principle is the combination of the offline trained prediction model and the online SEU measurement. The predicted rise of the SEUs is used to indicate the upcoming SPEs. The proposed system consists of four main building blocks operating in two phases:

Online phase – detection of the real-time SRAM SEUs in SEU measurement block, and prediction of the following SEUs in hardware accelerator block.

Offline phase – evaluation of the target SRAM SER (SEU rate) behaviour during historical solar events in the solar condition analysis block, and training of the prediction model in the model training block.

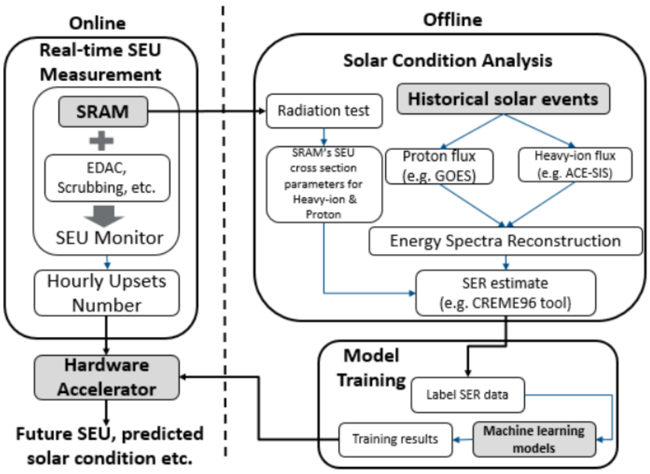

Fig. 1. Block diagram of the proposed SPE prediction method.

The real-time SEU rate measurement is conducted continuously during the mission. Important is to mention that the existing functional SRAM resources are used for SEU measurement. Although many previous SRAM-based particle monitors have been implemented as standalone chips, for the target safety critical applications is important that the particle monitor is close to the target system in order to detect the radiation conditions to which the target system is exposed. With the assistance of Error Detection And Correction (EDAC) and scrubbing mechanisms, the existing on-chip SRAM can be used to detect SEU rate without affecting its function as a storage element. A detailed description of this concept can be found in our previous work [6]. The total number of detected SEUs in each hour is stored and the hardware accelerator model processes the hourly SEU data for the prediction of the following upsets number.

In the solar condition analysis block, the hourly in-flight SER (SEU rate) of SRAM monitor (i.e. SER as function of time) is determined using experimentally obtained cross-section of target SRAM and hourly flux database obtained from previous space missions. In this case, according to the SPE list from the National Oceanic and Atmospheric Administration (NOAA) [12], all 36 SPEs during the solar cycle 24 (2008-2019) are selected for the analysis. The Geostationary Operational Environmental Satellite-Space Environment Monitor (GOES-SEM) [13] and Advanced Composition Explorer-Solar Isotope Spectrometer (ACE-SIS) [14] public databases have been used for proton and heavy-ion flux data source, respectively. The working environments for the GOES and ACE satellites are all close to the Earth in the heliosphere, but outside the Earth's geomagnetic influence. Therefore, the additional radiation impact from geomagnetically trapped protons and the shield protection from the Earth's magnetic field can be neglected during the following SER estimation. As a case study, a 2 Gbit COTS SRAM from Cypress, designed in 65 nm bulk CMOS technology, was selected as target SRAM. The proton and heavy-ion SEU cross-section data for the selected SRAM is available in [15]. Applying the methodology from [16], the energy spectra are reconstructed to avoid the issues of data gaps, low energy and incomplete ion type measurements from raw data. Then, the SRAM cross section and the energy spectra are processed by the CREME96 tool [17,18] to obtain the hourly SER data. Fig. 2 and Fig. 3 present a sample of the obtained proton-induced and heavy-ion-induced hourly SER from Jan 22 to 26, 2012, respectively. The observed SER for the target SRAM is the sum of the calculated proton and heavy-ion induced SER.

The acquired in-flight hourly SER data from historical solar events are processed, transformed as well as train and validate selected machine learning models in the model training block, which is discussed in Section III. The best performing machine learning model is to be implemented as the hardware accelerator, and combined with the SRAM-based SEU monitor for the on-line real-time prediction. Therefore, the expected upsets number of the SEU monitor in the following hour can be predicted, as described in Section IV. Since the SER of an electronic system exposed to radiation is linearly related to the particle flux [19], the predicted SER information can be used to estimate the SER of the target fault tolerant multi-processor system, but this is beyond the scope of this work.

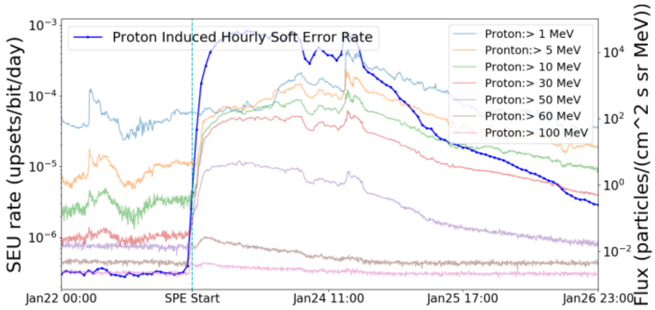

Fig 2. Proton-induced SER (SEU rate) from GOES database for Jan 22-26, 2012. The particle flux for all of the lower to higher energy channels are shown, and all channels are with good quality.

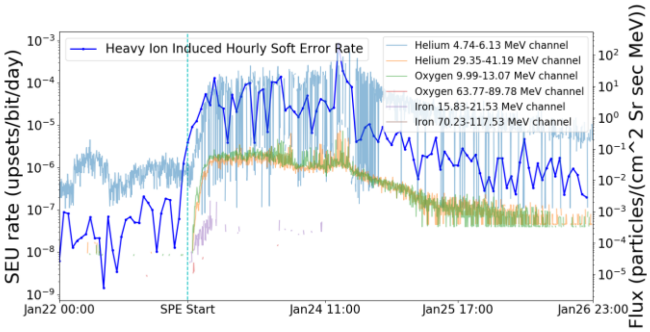

Fig. 3. Heavy-ion-induced SER (SEU rate) from ACE-SIS database for Jan 22-26, 2012. The particle ion flux of He, O and Fe for the lower and higher energy channels are shown, and high-energy channels data are of poor quality.

III. Machine Learning Model Selection

This section elaborates how machine learning techniques can be used to predict the in-flight upset rate of the SEU monitor in advance by using upset rates of the n_h last hours. This analysis is based on observations from a previous study [10] where several machine learning models have been evaluated to predict the hourly SER rate of an SRAM memory. In the mentioned study five regression models have been analyzed: (1) linear least squares, (2) decision tree, (3) k-nearest neighbors, (4) multi-layer perceptron (MLP) neural network and (5) recurrent neural network (RNN) with long short-term memory (LSTM). It has been observed that the RNN with LSTM model performed the best, but the linear least squares regression performed almost equally good. This is why in this paper the analysis focuses only on these two models.

To perform the prediction first, the in-flight hourly SER data acquired from historical solar events is processed and transformed in order to be representative to actual upsets obtained from the SEU monitor (see section II). The machine learning regression model is trained with this transformed data acquired from historical solar events. Then the prediction of the hourly upset rate by the trained model is evaluated.

A. *Pre-processing of the Test and Training Data Set*

The in-flight hourly SER data acquired from historical solar events forms the test and training data set for the machine learning models. The hourly SER values obtained are obtained by processing the hourly flux database, as explained in section II. The energy spectra of the flux data is reconstructed and together with the SRAM cross-section and the CREME96 tool the SEU/bit/day is calculated. In the actual system the data from the SEU monitor will be an integer number from 0 to the size of the SRAM. To get this number of hourly upsets, the SEU/bit/day values are divided by 24h and multiplied by the SRAM size.

Moreover, it is known that most Machine Learning models work best when the input data is in the range from 0 to 1. To achieve this, the actual number of upsets is divided by the next power of two of the highest expected numbers of upsets. In this way, no actual division need to be implemented in hardware since it is just a different representation of the input data as fixpoint integer.

B. *Model training*

This processed and transformed data is used to train and evaluate the Machine Learning models in a supervised manner. The data set was split, whereas 60% of the data is used for training and the remaining 40% of the data is used for the evaluation.

During the training process, the internal parameters of the Machine learning models are adjusted and optimized by the machine learning algorithm. In addition to these internal parameters, most of the machine learning models have so called hyperparameters to control properties of the machine learning model. These hyperparameters however, are not determined by the training algorithm and are usually set manually before the training process. The problem of finding the optimal set of hyperparameters is called hyperparameter optimization. To obtain the optimal set, several instances of the model are trained and evaluated for different sets of hyperparameters. In this paper, first the model is evaluated for randomly generated parameter values in a given distribution. Afterwards a more detailed grid search is performed within the region of the values obtained by the random search.

A different parameter which needs to be optimized for the given problem is the optimal length n_h for the past hourly SEU values needs to be determined. Therefore, models were also evaluated for different history length of the hourly SEU data.

C. *Model evaluation and comparison*

The performance of selected models was evaluated in terms of Mean Absolute Error (MAE), Maximum Absolute Error (MAX), Root Mean Square Error (RMSE) and the coefficient of determination (R^2) score. These scores were calculated on the predicted test data set of the trained model. In order to obtain a more stable measurement a cross-validation of 10 was used. This means, the data set is split into 10 different train and test data sets which were used to independently train and evaluate the models. The scores were averaged over the different measurements obtained by applying the different sets. In this way, it is avoided that particularly good or bad training and test data sets are used.

The model performance was measured for different length of the past hourly SEU data n_h, varying between 3h and 24h. For each considered n_h the above described hyperparameter optimization was performed and the model performance was measured with the mentioned metrics. Fig. 4 and Fig 5 show performance of the two considered models in terms of R^2 and RMSE respectively. It can be seen that both models have a high accuracy and the RNN performs slightly better than the Linear Least Squares model. The best performances are obtained with a past hourly SEU data n_h of 14 for the RNN model and 17 for the linear least squares model.

Although the RNN model might perform slightly better, the Linear Least Square model has the advantage that it is much simpler and uses significantly less resources than the RNN model. Therefore, the Linear Least Square model has been chosen for the hardware accelerator in the following sections.

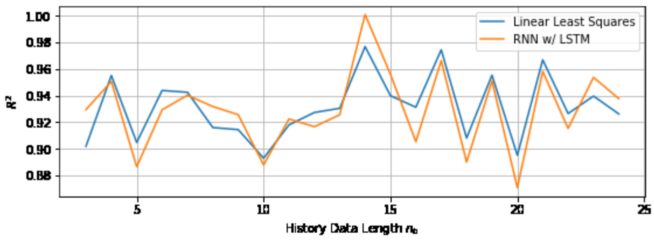

Fig. 4. R^2 score (higher the better) for the Linear Least Squares and RNN regression models with varying history data length n_h.

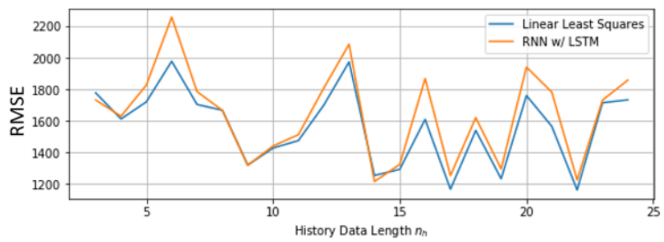

Fig. 5. RMSE (lower the better) for the Linear Least Squares and RNN regression models with varying history data length n_h.

IV. Hardware Accelerator Design

The hardware accelerator implements the machine learning algorithm based on the linear regression model. The proposed design is intended to collaborate with an SRAM-based SEU monitor and offline-trained results from selected machine learning model. Fig. 4 shows the block diagram of the hardware accelerator design as well as the connection with collaboration models. Two register files record the detected real-time hourly SEU data from the monitor and the trained parameter results from the offline machine learning model, respectively. An accumulator is used to implement the needed calculation. A simple control logic selects the inputs and the functionality of the accumulator. The right shifter processes the calculated result from the accumulator to obtain the predicted SEU data.

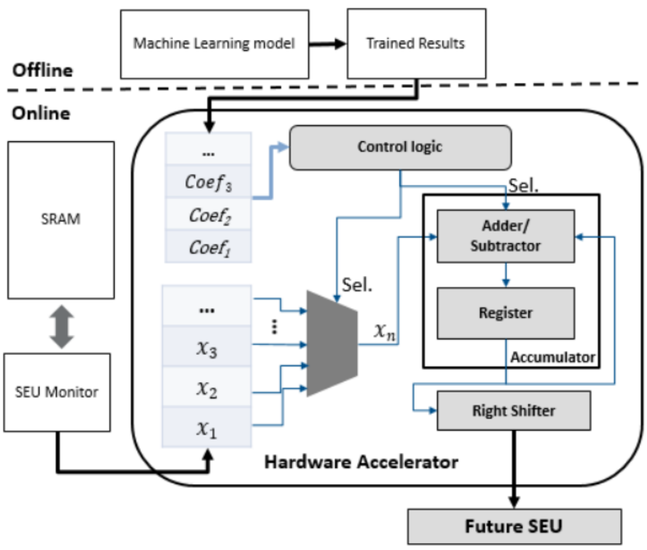

Fig. 4. Proposed hardware accelerator structure with accessories.

According to the trained results from Section III, the best accuracy of the SEU prediction can be obtained when the history data length is set to 17. Therefore, the corresponding prediction function for this case is:

$$SEU_{pred\_acc} = 1.2929 * x_1 + 0.0868 * x_2 + (-1.1946) * x_3 + 1.0308 * x_4 + 0.1016 * x_5 + (-0.9142) * x_6 + 0.8201 * x_7 + (-0.0178) * x_8 + (-0.6824) * x_9 + 0.6575 * x_{10} + (-0.0204) * x_{11} + (-0.4687) * x_{12} + 0.4181 * x_{13} + (-0.0271) * x_{14} + (-0.2207) * x_{15} + 0.1815 * x_{16} + (-0.0732) * x_{17} \quad (1)$$

The coefficients of the above equation are obtained from the trained linear regression machine learning model. The x_n in function (1) stands for the detected hourly SEU number from the monitor in n hours ago, which also means that the prediction function can start to work after the monitor consecutively works and records the 17-hour data. Since this design is intended to be used as an embedded part of space-borne system, simplicity and flexibility are among the most important concerns. Thus, to avoid floating point calculation and reduce the hardware complexity, the coefficients in function (1) are magnified by 2^n times and only taking the integer part to simplify the equation. The magnification factor needs to ensure that the new prediction equation induced accuracy variation is less than 1%. In this study, the magnification factor 32 is used, and the corresponding prediction function is as follow:

$$SEU_{pred\_acc\_32} = (41 * x_1 + 3 * x_2 + (-38) * x_3 + 33 * x_4 + 3 * x_5 + (-29) * x_6 + 26 * x_7 + (-1) * x_8 + (-22) * x_9 + 21 * x_{10} + (-1) * x_{11} + (-15) * x_{12} + 13 * x_{13} + (-1) * x_{14} + (-7) * x_{15} + 6 * x_{16} + (-2) * x_{17}) / 2^5 \quad (2)$$

Two 32 * 21-bit address register files are used for logging the historical SEU data and prediction function coefficients, respectively. Regarding the historical SEU data register file, a single 21-bit entry consists of a valid entry bit, and a 20-bit representing the number of detected upsets. According to the historical solar events analysis for the solar cycle 24, which is mentioned in Section II, the peak value for the hourly upsets count of the target SRAM is 118122 upsets/hour/2G-bit. Therefore, the size of the selected register file can guarantee regular data storage even during large SPE peak fluxes. Moreover, up to 32 historical hourly upset records can be thus stored simultaneously. If the register file overflows, the oldest individual record will be automatically discarded. For the coefficients register file, the contents are loaded during the system setup and rarely updated during the system operation. After being magnified, as shown in function (2), the coefficients are stored in each row, separately. A single 21-bit entry consists of a valid entry bit, a sign bit and a 19-bit digit.

The accumulator is used to replace the multiplication operation in prediction function by repeated addition calculations. Therefore, a much longer calculation time than the traditional multiplier is expected. In this study, for function (2), a total of 262 clock cycles is needed in the accumulator. Therefore, the minimum required time for the calculation of function (2) is 5.24 µs when the working frequency is 50 MHz. Considering that the historical SEU data register file is updated every hour, which means this calculation is required only once every hour, the calculation speed for the accumulator is sufficient for the current study. The accumulator contains a 32-bit full-adder, one two's

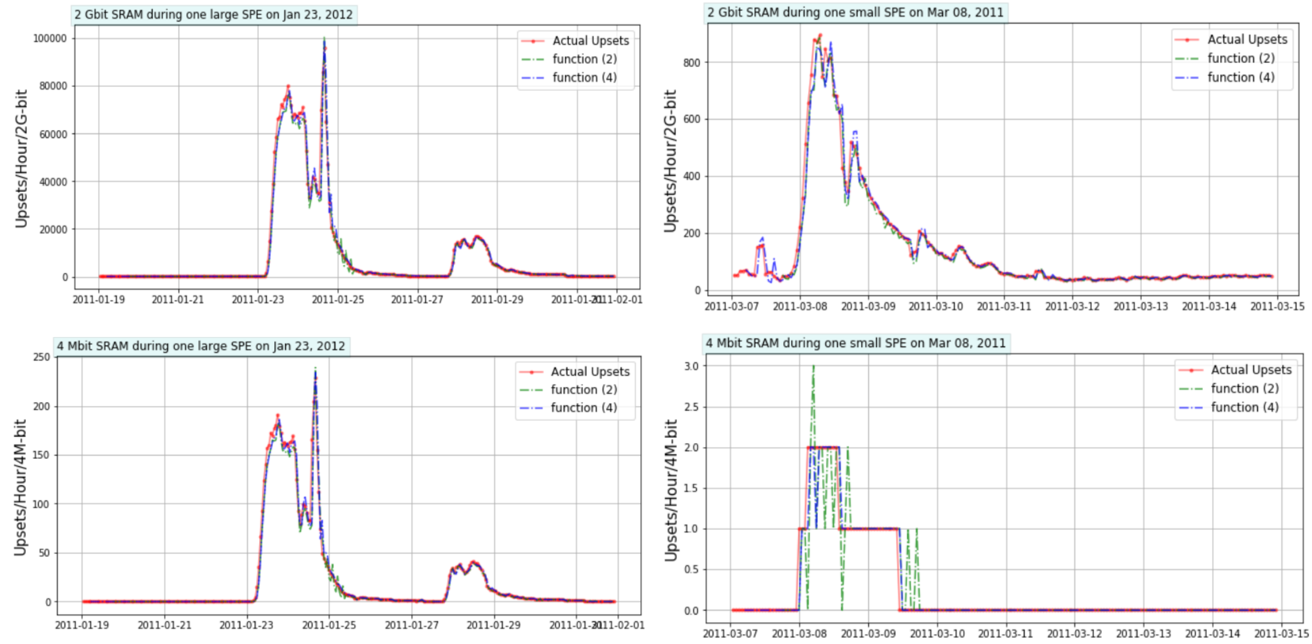

Fig. 5. Hardware accelerator SEU prediction performance for 2Gbit and 4 Mbit SRAM during large and small SPEs, respectively. The function (2) is the prediction function with history data length 17 and magnification factor 32. The function (4) represents the prediction with history data length 4 and magnification factor 1024.

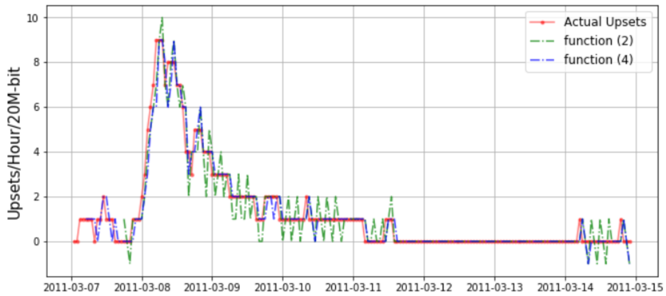

Fig. 6. Hardware accelerator SEU prediction performance for 20 Mbit SRAM during a small SPE on Mar 08, 2011.

complement number converter and a 32-bit register. The register keeps the intermediate arithmetic result from the adder. The inputs for adder are the selected x_n and previous results from the register. Moreover, the selected x_n is converted to the two's complement form when the corresponding coefficient identifies a subtraction operation. Considering the calculation in practical applications, the overflow is not expected.

The control logic is manipulated by the coefficients to select the appropriate x_n for accumulator as well as determine the number of repetitions. The right shifter is used to shrink the calculation result based on the previous magnified factor, which is 5-bit right shift in this study. Moreover, the hardware accelerator can also be affected by radiation particles, thus, Triple-Modular Redundant (TMR) flip-flops are used in order to enhance their robustness against SEUs [20].

V. ANALYSIS OF RESULTS

A. Prediction Performance Analysis

In this section, the impact of SRAM size and history data size on the prediction performance are analyzed. The analysis in Section III was done for a large size SRAM with a size of 2 Gbit and with history data length of 17. However, many embedded systems do not have the multi-Gbit SRAM resources, but rather much smaller internal SRAM with the size from several Mbit to tens of Mbit. In such a case, the small detection area of the SRAM may not provide sufficient sensitivity, and it is necessary to evaluate the optimal SRAM size that is required for particle detection. Moreover, the selection of history data length of 17 means the prediction cannot be done for the first 17 hours, which may be too long for some scenarios where faster prediction is required. According to the history data length analysis in Section III, length 4 also has an excellent R^2 score with a slightly worse RMSE performance. For this case, the prediction equation is:

$$SEU_{pred\_fast} = 1.1939 * x_1 + 0.1105 * x_2 + (-0.7789) * x_3 + 0.4478 * x_4 \quad (3)$$

The magnification factor 1024 is used for the above function, thus, the corresponding function implemented in hardware accelerator is:

$$SEU_{pred\_fast\_1024} = (1223 * x_1 + 113 * x_2 + (-798) * x_3 + 459 * x_4) / 2^{10} \quad (4)$$

In Figure 5, the hardware accelerator SEU prediction performance for functions (2) and (4) applied to 2 Gbit and 4 Mbit SRAMs, during large and small SPEs, is illustrated. The SEU rate for the assumed 4 Mbit SRAM was determined by scaling the SEU rate for 2 Gbit, where the scaling factor is the size ratio of the two SRAMs. Although this a rough estimate, it is valid for comparison because the SEUs of an SRAM is proportional to its size.

It can be seen that both functions (2) and (4) can predict the SEU variation accurately for the small and large SPEs with 2 Gbit SRAM. However, with 4 Mbit SRAM only the large SPE can be predicted while neither of these equations can work well during a small SPE. The main reason is that the SEU monitor with 4 Mbit SRAM does not have sufficient resolution to provide valid SEU data for prediction during the SPE on-set period.

In Fig. 6, the prediction performance for 20 Mbit SRAM during the same small SPE as previous is shown. It can be seen that the 20 Mbit SRAM can predict the small SPEs. In addition, due to not considering too much historical SEU data with low resolution, the function (4) has a better prediction performance than function (2). In order to get a smoother prediction curve than in Fig. 6 and thus ensure good quality of SPE prediction, a larger SRAM area needs to be used.

B. Synthesis Results

Since the hardware accelerator is intended to be implemented together with SRAM and SEU monitor on a single chip, it is essential to investigate the introduced overheads of the power and area. The following synthesis results are for the IHP's 130 nm bulk CMOS technology with the supply voltage of 1.2V, and the operating nominal frequency of 50 MHz. Although the synthesis analysis in this section uses different technology than the analyzed SRAM, the results are of significant value for hardware consumption comparison because the proposed design is general and can be implemented in different technologies. The choice of the target technology will define the SRAM's cross-section which is obtained from irradiation experiments.

Tables I shows the total power and area comparison for 20 Mbit SRAM, SEU monitor and proposed hardware accelerator. Even though the introduced area and power consumption of proposed hardware accelerator is about 10 times larger than the SEU monitor, compared with 20 Mbit SRAM, the induced power and area consumption are only 0.8% and 4.5%, respectively. Therefore, the results show that the cost and overhead for the hardware accelerator are negligible compared to the host SRAM.

TABLE I. AREA (IN mm^2) AND POWER (IN mW) COMPARISON

	Area	Power
20 Mbit SRAM	14	384
SEU Monitor	0.0957	0.211
Hardware Acc.	0.642	3.23

VI. CONCLUSION AND FUTURE WORK

A low-cost hardware accelerator for the in-flight SEU variation prediction of the on-board SEU monitor system for space applications is presented. The upcoming large flux event, such as SPE, can be indicated from the predicted rise of SEU rate at least one hour in advance. Moreover, the fine-grained hourly tracking of SEU variations is supported. The concept combines the online SEU prediction with an SRAM-based particle detector and supervised machine learning prediction model trained offline with publicly available flux databases from past space missions. Our analysis has shown that the linear regression machine learning model has a very good prediction accuracy for the analyzed application, and can be implemented in the hardware accelerator with a negligible cost.

There are still open issues which have to be addressed in future work. Firstly, the accuracy of the prediction model can be further improved and the prediction time can be extended beyond one hour. The accuracy can be improved by providing the real-time measurement of particle LET, which can be used as additional input parameter for the machine learning algorithm. Furthermore, it is necessary to integrate the SEU monitor and the hardware accelerator proposed in an adaptive multicore system on a single chip, and establish a model for estimating the SER of the multicore system in terms of the SER of SEU monitor.

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REFERENCES

[1] E. Petersen, "Single Event Effects in Aerospace". Wiley-IEEE Press, 2011.

[2] J. L. Barth et al., "Space, Atmospheric and Terrestrial Radiation Environments," IEEE Transactions on Nuclear Technology, Vol. 50, No. 3, pp. 466 – 482, 2003.

[3] D. L. Hansen et al., "Correlation of Prediction to On-Orbit SEU Performance for a Commercial 0.25-µm CMOS SRAM," in IEEE Transactions on Nuclear Science, vol. 54, no. 6, Dec. 2007, pp. 2525-2533.

[4] K. H. Yearby et al., "Single-event upsets in the cluster and double star digital wave processor instruments," in Space Weather, vol. 12, no. 1, Jan. 2014, pp. 24-28.

[5] A. Simevski, O. Schrape, C. Benito, M. Krstic, M. Andjelkovic, "PISA: Power-robust Microprocessor Design for Space Applications," in Proc. /IOLTS, 2020.

[6] J. Chen et al., "Design of SRAM-Based Low-Cost SEU Monitor for Self-Adaptive Multiprocessing System," In Proc. 22nd Euromicro Conference on Digital System Design (DSD), Kalithea, Greece, 2019.

[7] E. Camporeale, "The challenge of machine learning in Space Weather: Nowcasting and forecasting", Space Weather, vol. 17, 2019.

[8] H. M. Bain, P. Brea, E. T. Adamson, "Using Machine Learning Techniques to Forecast Solar Energetic Particles," in Proc. SOARS, 2018.

[9] A. J. Engell et al., "SPRINTS: A Framework for Solar-Driven Event Forecasting and Research," Space Weather, 2017.

[10] J. Chen, T.Lange, M. Andjelkovic, A. Simevski, M.Krstic, "Prediction of Solar Particle Events with SRAM-Based Soft Error Rate Monitor and Supervised Machine Learning," in Proc. ESREF, 2020 (accepted paper).

[11] V. Sze, Y. Chen, T. Yang and J. S. Emer, "Efficient Processing of Deep Neural Networks: A Tutorial and Survey," in Proceedings of the IEEE, vol. 105, no. 12, pp. 2295-2329, Dec. 2017.

[12] National Oceanic and Atmospheric Administration (NOAA) solar proton events affecting the earth environment lists web page: https://ngdc.noaa.gov/stp/satellite/goes/doc/SPE.txt

[13] Geostationary Operational Environmental Satellites (GOES) - Space Environment Monitor (SEM) database web page: https://ngdc.noaa.gov/stp/satellite/goes/dataaccess.html

[14] Advance Composition Explorer (ACE) - Solar Isotope Spectrometer (SIS) database web page: http://www.srl.caltech.edu/ACE/ASC/level2/lvl2DATA_SIS.html

[15] V. Gupta, "Analysis of single event radiation effects and fault mechanisms in SRAM, FRAM and NAND Flash : application to the MTCube nanosatellite project", PhD dissertation, University of Montpellier, 2017.

[16] S. E. Hoyos, H. D. R. Evans and E. Daly, "From Satellite ion flux data to SEU rate estimation," in IEEE Transactions on Nuclear Science, vol. 51, no. 5, pp. 2927-2935, Oct. 2004.

[17] A. J. Tylka et al., "CREME96: A revision of the cosmic ray effects on Micro-electronics code," IEEE Trans. Nucl. Sci. vol. 44, no. 6, pp. 2150–2160, Dec. 1997.

[18] Creme96 suit web page: https://creme.isde.vanderbilt.edu/

[19] P. Hazucha, C. Svensson, "Impact of CMOS Technology Scaling on the Atmospheric Neutron Soft Error Rate," IEEE Trans. on Nuclear Science, 2000.

[20] V. Petrovic and M. Krstic. "Design flow for radhard TMR Flip-Flops," Design and Diagnostics of Electronic Circuits and Systems, IEEE International Symposium on, 2015, pp. 203.