Energy Aware Real-Time Scheduling Policy with Guaranteed Security Protection

Wei Jiang¹, Ke Jiang², Xia Zhang¹, Yue Ma³

¹School of Information and Software Engineering University of Electronic Science and Technology of China ²Department of Computer and Information Science Linköping University, Sweden ³Department of Computer Science and Engineering University of Notre Dame, USA







Embedded system design concerns



The Design Problem

- Security- & Energy-aware Real-Time Application
- System execution goal
 - Complete the App. with minimal energy
 - Satisfy the security and real-time requirements
- NP-hard to find the best solution

The Method

 Dynamic Programming based Approximate optimization framework

Outline

- Motivational application
- System model
- Problem formulation
- Approximation based Dynamic Programming
- Experimental results
- Conclusion

Motivational application



System Model

Architecture model

Mono-processor, Battery powered

Application model

- A set of periodic security- & energy-aware tasks
- Security risk constraint
- Scheduling by classic method, e.g. RM/EDF

Task model

- A mandatory and optional part (Security improve)
- Task attributes: $(BE_i, P_i, L_i, S_i, S_i^{DM}, V_i, SR_i)$

Security Overhead Model

Measure energy & time of security algorithms



Security Overhead Model

Measurement results

Ciphers	time(ms/KB)	Energy(mJ/KB)	Sec. Level	
RC4	0.0063	0.0007	4	
RC5	0.0125			
BLOWFISH	0.0170	Energy/time ratio: 320 mJ/S		
IDEA	0.0196		`	
SKIPJACK	0.0217	POW (power)		
3DES	0.0654	21.0914	6	

Execution time of each task

• $Exe_i = BE_i + \theta(S_i) * L_i$

Energy consumption of each task

•
$$En_i = POW * (BE_i + \theta(S_i) * L_i)$$

Security Risk Model of each task

Definition

 Security risk (SR) is the product of security failure probability and consequence impact of security failure.

$$\blacksquare SR_i = Pro_i^{risk} * V_i$$

Failure probability

•
$$Pro_i^{risk} = \begin{cases} 0, & if S_i \ge S_i^{DM} \\ 1 - e^{-\lambda_i (S_i^{DM} - S_i)} \end{cases}$$

More reasonable than other linear security QoS definitions like ref. [8, 10]

Original problem

$$\begin{array}{ll} \text{Min} & \text{Energy} = \sum_{i=1}^{N} \left(\frac{HP}{P_i}\right) * En_i \\ \\ \text{S.T.} & \begin{cases} \sum_{i=1}^{N} \left(\frac{HP}{P_i}\right) * SR_i \leq RB \\ \sum_{i=1}^{N} (BE_i + \theta(S_i) * L_i)/P_i \leq UB_x \\ S^{min} \leq S_i \leq S^{max} \end{cases} \end{array}$$

• Energy =
$$\sum_{i=1}^{N} \left(\frac{HP}{P_i}\right) * En_i$$

= $HP * POW * \sum_{i=1}^{N} (BE_i + \theta(S_i) * L_i)/P_i$

Reduced problem

- Min. Utilization
- Risk constraint
- Utilization cons We don't need to consider
- Security level c Energy dimension!

Proposed Optimization Technique

Markov dynamic programming procedure

Approximating policies and analysis

Round Nearest approximating algorithm

Low Time complexity

Markov decision-making procedure

- Multi-stage decision procedure Accumulated utilization ratio of first *i* tasks
 - N-Stage (One task, one stage)
 - Decision variable: S_i (Accumulated risk of first *i* tasks
 - State definition: $(\xi_{ik}, \gamma_{ik}, S_{ik})$ Specific *level* for *k*-th state



Multi-stage decision-making procedure

- Number of states increases exponentially! How next?
- Approximation of Knapsack problem
 - Scale risk into a series of discrete integers by Δ
 - Replace states with same risk by lowest utilization one
 - States denoted by a $N \times M$ matrix, $M = [RB/\Delta]$

0	1	2	12222	M
T_1	$(\xi_{l,1}, \gamma_{l,1}, S_{l,1})$	$(\xi_{1,2}, \gamma_{1,2}, S_{1,2})$		$(\xi_{1,\mathcal{M}},\gamma_{1,\mathcal{M}},S_{1,\mathcal{M}})$
<i>T</i> ₂	$(\xi_{2,1}, \gamma_{2,1}, S_{2,1})$	$(\xi_{2,2},\gamma_{2,2},S_{2,2})$		$(\xi_{2,M},\gamma_{2,M},S_{2,M})$
	19292	10.00		2022/0
T_{N-1}	$(\xi_{\rm N-1,1}, y_{\rm N-1,1}, S_{\rm N-1,1})$	$(\xi_{v-1,2}, \gamma_{v-1,2}, S_{v-1,2})$		$(\xi_{\rm NH, dir}, \gamma_{\rm NH, dir}, S_{\rm NH, dir})$
T_N	$(\xi_{N\downarrow},\gamma_{N\downarrow},S_{N\downarrow})$	$(\xi_{N,2},\gamma_{N,2},S_{N,2})$		$(\xi_{N,M},\gamma_{N,M},S_{N,M})$

Approximating policies and analysis

- Round to Ceiling (RC) $RC(SR_i) = \left\lceil \frac{SR_i}{\Delta} \right\rceil$
- Round to Floor (RF) $RF(SR_i) = \left\lfloor \frac{SR_i}{\Delta} \right\rfloor$

$$RC(2.2) = 3$$

Err = 0.8

Err = 0.8

$$RF(2.8) = 2$$

Round Randomly (RR)

 $RR(SR_i) = \begin{cases} \left[\frac{SR_i}{\Delta}\right] \text{with probability } \rho_1 = \frac{SR_i}{\Delta} - \left\lfloor\frac{SR_i}{\Delta}\right\rfloor \\ \left\lfloor\frac{SR_i}{\Delta}\right\rfloor \text{with probability } \rho_2 = \left\lceil\frac{SR_i}{\Delta}\right\rceil - \frac{SR_i}{\Delta} \end{cases}$

Round to Nearest (RN)

$$RN(SR_i) = SR_i^{\Delta} = \begin{cases} \begin{bmatrix} \frac{SR_i}{\Delta} \end{bmatrix}, & \text{if } \frac{SR_i}{\Delta} - \lfloor \frac{SR_i}{\Delta} \rfloor \ge 0.5 \\ \lfloor \frac{SR_i}{\Delta} \rfloor, & \text{if } \frac{SR_i}{\Delta} - \lfloor \frac{SR_i}{\Delta} \rfloor < 0.5 \end{cases} \quad \frac{RN(2.2) = 2}{RN(2.8) = 3}$$

Approximating policies and analysis

- How to determine Δ , given $(1 + \beta) * RB$ approximation?
- Overall Deviation for N tasks is:
 - $OD^{RC} \ge -N\Delta$
 - $OD^{RF} \leq N\Delta$
 - $-N\Delta \le OD^{RR} \le N\Delta$
 - $-N\Delta/2 \le OD^{RN} \le N\Delta/2$
- For $(1 + \beta)$ approximation, $|OD| \le \beta \cdot RB$

- Max
 <u>A</u> of RN is twice larger than RF, RC and RR!
 - Reduce the number of states by a half in decision-making procedure !

Round Nearest approximating algorithm

Algorithm 1 RN-based approximation algorithm

1: Step 1: Schedulability test 2: if $\sum_{i=1}^{N} (HP/P_i)SR_i(S^{max}) > RB$ or $\sum_{i=1}^{N} Exe_i(S^{min})/P_i > UB_x$ then 3: Return. /*Given task set is not schedulable*/ 4. 5: Step 2: Initialization 6: Compute the grouping factor $\Delta = 2\beta RB/N$ and M = $[RB/\Delta]$ 7: Initialize state matrix $\Omega_{N\times M}$ with each element $\Omega_{i,j} = (0,0,0)$ 8: Initialize Ω_1 by calculate (ξ_1, γ_1, S_1) with each $S_1 \in$ [S^{min}, S^{max} Q. 10: Step 3: Update the state matrix in N-Stage decision procedure 11: for i = 2 to N do while $(\xi_{i-1}, \gamma_{i-1}, S_{i-1}) \neq (0, 0, 0)$ in Ω_{i-1} do for $S'_i = S^{min}$ to S^{max} do 12: 13: Calculate temporary state $(\xi'_i, \gamma'_i, S'_i)$ 14: if $\xi'_i > UB_x$ or $\gamma'_i > RB$ then 15: Ignore this state and break /*Schedulability or security 16: violated*/ if state $\Omega_{i,j}$, $(j = \gamma_i)$ is not existed then 17: $\Omega_{i,j} = (\xi'_i, \gamma'_i, S'_i)$ /*Store new state*/ 18: else if $\xi'_i < \xi_i$ in $\Omega_{i,j}$ then $\Omega_{i,j} = (\xi'_i, \gamma'_i, S'_i)$ /*Keep state with smaller utiliza-19: 20: tion*/ 21. 22: Step 4: Find the minimal energy consumption solution 23: Find $\Omega_{N,i}^*$ with minimal utilization ratio ξ_N^* 24: Obtain the final security assignment decision (S_1, S_2, \dots, S_N)

by backtracking

25: $Energy^* = \xi_N^* * HP * POW /*The minimal energy*/$

Experimental results

Experiment setup

- Two group simulations, each with three synthetic sets
- Basic execution time of each task: 5~10 ms
- Period: 300~500 ms
- Confidential data size: 100~400 KB
- Security demand: 6~8
- Security impact/loss of each task: 5~10 \$
- Security coefficient λ : 1~3

Compared algorithms

- RRAA: Round Randomly approximating algorithm
- RCAA [16]: Round to Ceiling approximating algorithm
- GRDY: Assigned security level in greedy fashion
- SEAS [8]: Gradually increase the security by small risk/energy ratio

Impacts of Risk Bound (RB)

• $RB = MIR + \alpha * (MAR - MIR), \beta = 0.05$



Impacts of Risk Slack Ratio (β)

• Given RB = MIR + 0.7 * (MAR - MIR)



- A new scheduling optimization problem for securityand energy-critical real-time applications
 - Minimal energy with real-time and risk constraints
 - Multi-dimensional knapsack problem (NP-hard)
- Efficient techniques
 - Problem reduced (energy dimension)
 - Approximating dynamic programming
 - Half complexity of traditional approx. DP algorithms
- Experiments show the good performance



Thanks for your time!