

# On the minimal value set size of APN functions

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## Abstract

We give a lower bound for the size of the value set of almost perfect nonlinear (APN) functions  $F: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  in explicit form and prove it with methods of linear programming. It coincides with the bound given in [5]. For  $n$  even it is  $\frac{2^n+2}{3}$  and sharp as the simple example  $F(x) = x^3$  shows. The sharp lower bound for  $n$  odd has to lie between  $\frac{2^n+1}{3}$  and  $2^{n-1}$ . Sharp bounds for the cases  $n = 3$  and  $n = 5$  are explicitly given.

**Keywords** Boolean functions, Cryptographic S-boxes, Almost perfect nonlinear (APN), Size of value set

**Mathematics Subject Classification (2020)** 94A60, 06E30, 11T71

## 1 Introduction

Almost perfect nonlinear (APN) functions are quite important in cryptography. Due to their optimal resistance to differential attacks [10] they are used as S-boxes of block ciphers. An introduction to the topic can be found in the book [6] and in the survey [1].

In general, a better understanding of APN functions could be helpful to find new APN functions. Therefore, we will have a closer look at the size of the value set of an APN function and present here a lower bound in explicit form. It coincides with the bound given in [5] but instead of proofing it with the Cauchy-Schwarz inequality we use the duality theorem of linear programming.

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In Section 2 we will introduce some basic definitions and have a look at some properties of preimages of APN functions. Afterwards in Section 3 we will state our main theorem about the minimal size of the value set of an APN function and present both theoretical derivations, and a summary of our computational results.

## 2 Preliminaries

Let  $\mathbb{F}_2^n$  be the vector space of dimension  $n$  over the finite field with two elements  $\mathbb{F}_2 = \{0, 1\}$ . We denote  $\mathbb{F}_{2^n}$  when it is endowed with its finite field structure.

The *value set* of a (vectorial Boolean) function  $F: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  is defined by  $V_F = \{F(x) : x \in \mathbb{F}_2^n\}$ , its size (or cardinality) is denoted by  $|V_F|$  and  $F^{-1}(y) = \{x \in \mathbb{F}_2^n : F(x) = y\}$  is the *preimage* of  $y \in \mathbb{F}_2^n$  of  $F$ .

A function  $F: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  is called *almost perfect nonlinear (APN)* if, for every nonzero  $c \in \mathbb{F}_2^n$  and every  $d \in \mathbb{F}_2^n$ , the equation  $F(x + c) + F(x) = d$  has at most two solutions [10].

There are several equivalence relations on functions that preserve properties like that of being APN or like the size of its value set. Two functions  $F, G: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  are called:

1. *affine equivalent* if  $G = T_1 \circ F \circ T_2$  where the functions  $T_1, T_2: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  are affine permutations;
2. *extended affine (EA) equivalent* if  $G = T_1 \circ F \circ T_2 + A$  where the functions  $T_1, T_2: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  are affine permutations and  $A: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  is an affine function.

Affine equivalence is a special case of EA equivalence. The APN property of a function is preserved by EA equivalence [11, 4]. It is straightforward to show that the size of a value set is preserved by affine equivalence but not in general by EA equivalence.

Let us take a closer look at some properties of the preimages of APN functions. We define

$$S_2(M) = \{m_1 + m_2 : m_1, m_2 \in M \text{ and } m_1 \neq m_2\}$$

for  $M \subseteq \mathbb{F}_2^n$ . The union of two disjoint sets  $M_1, M_2$  is denoted by  $M_1 \cup M_2$ .

**Proposition 2.1.** *Let  $F: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  be a function. If  $F$  is APN then*

$$\bigcup_{y \in \mathbb{F}_2^n} S_2(F^{-1}(y)) \subseteq \mathbb{F}_2^n \setminus \{0\}$$

and

$$|S_2(F^{-1}(y))| = \binom{|F^{-1}(y)|}{2}$$

for  $y \in \mathbb{F}_2^n$ .

*Proof.* It follows immediately from the definition that  $0 \notin S_2(F^{-1}(y))$  for  $y \in \mathbb{F}_2^n$ .

Suppose that  $S_2(F^{-1}(y_1)) \cap S_2(F^{-1}(y_2)) \neq \emptyset$  for  $y_1, y_2 \in \mathbb{F}_2^n$ ,  $y_1 \neq y_2$ . Hence there exist  $c \in \mathbb{F}_2^n \setminus \{0\}$  and  $x_1, x_2 \in \mathbb{F}_2^n$ ,  $x_1 \neq x_2$  such that  $F(x_1) = F(x_1 + c) = y_1$  and  $F(x_2) = F(x_2 + c) = y_2$ . But then it follows that  $F(x_1) + F(x_1 + c) = F(x_2) + F(x_2 + c) = 0$  and  $F$  is not APN.

Suppose that  $|S_2(F^{-1}(y))| < \binom{|F^{-1}(y)|}{2}$  for  $y \in \mathbb{F}_2^n$ . Hence there exist  $x_1, x_2, x_3, x_4 \in F^{-1}(y)$  pairwise different with  $x_1 + x_2 = x_3 + x_4$ . Thus,  $F(x_1 + (x_1 + x_2)) + F(x_1) = F(x_3 + (x_3 + x_4)) + F(x_3) = 0$  and  $F$  is not APN.  $\square$

We remark that Proposition 2.1 cannot be used to characterise APN functions e.g if  $F: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  is bijective. In this case we have  $S_2(F^{-1}(y)) = \emptyset$  for  $y \in \mathbb{F}_2^n$ . But it is quite useful to find a lower bound for the size of the value set of an APN function.

For a function  $F: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  we define

$$k_i = |\{y \in \mathbb{F}_2^n : |F^{-1}(y)| = i\}|$$

for  $1 \leq i \leq 2^n$  and call the vector  $(k_i)_{1 \leq i \leq 2^n}$  the *preimage size distribution* of  $F$ . Since  $\mathbb{F}_2^n = \cup_{y \in \mathbb{F}_2^n} F^{-1}(y)$ , it follows

$$2^n = \sum_{i=1}^{2^n} i k_i. \quad (1)$$

If  $F$  is additionally APN then

$$2^n - 1 \geq \sum_{i=1}^{2^n} \binom{i}{2} k_i, \quad (2)$$

by Proposition 2.1. Subtracting (1) from (2) leads to the following result:

**Corollary 2.2.** *If  $F$  is APN then*

$$k_1 + k_2 \geq 1 + \sum_{i=4}^{2^n} \frac{i(i-3)}{2} k_i. \quad (3)$$

Consequently, there always exists  $y \in \mathbb{F}_2^n$  such that  $|F^{-1}(y)|$  equals 1 or 2.

### 3 Minimal size of value set

We will now present our main theorem and proof it with the duality theorem of linear programming. Lemma 5 of [5] gives an equivalent bound but proved using the Cauchy-Schwarz inequality. Just recently, after finishing the first version of this paper, [7] and [9] generalised this result to more classes of functions. In both generalisations the bound for the APN case coincides with the one given in this paper.

**Theorem 3.1** ([5]). *Let  $F: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  be a function. If  $F$  is APN then*

$$|V_F| \geq \begin{cases} \frac{2^n+1}{3} & \text{for } n \text{ odd,} \\ \frac{2^n+2}{3} & \text{for } n \text{ even.} \end{cases}$$

*Proof.* We translate (1) and (3) into a linear programming problem.

**Primary Problem:** Minimize

$$k_1 + \cdots + k_{2^n}$$

with  $k_i \in \mathbb{Q}$  and  $k_i \geq 0$  for  $1 \leq i \leq 2^n$  such that (1) and (3) holds.

**Dual Problem:** Maximize

$$-2^n l_1 + l_2$$

with  $l_1, l_2 \in \mathbb{Q}$  and  $l_2 \geq 0$  such that

$$j l_1 + \frac{j(j-3)}{2} l_2 \geq -1$$

for each  $1 \leq j \leq 2^n$ .

From the duality theorem of linear programming (e.g. Corollary 7.1g in [12]) it follows that the feasible solutions

$$k_2 = 1, k_3 = \frac{2^n - 2}{3}, k_i = 0 \text{ otherwise}$$

$$l_1 = -\frac{1}{3}, l_2 = \frac{1}{3}$$

are optimal since

$$-2^n \left(-\frac{1}{3}\right) + \frac{1}{3} = \frac{2^n + 1}{3} = 1 + \frac{2^n - 2}{3}.$$

For  $n$  odd it follows  $k_3 = \frac{2^n-2}{3} \in \mathbb{Z}_{\geq 0}$ . For  $n$  even the feasible solution

$$k_1 = 1, k_3 = \frac{2^n - 1}{3} \in \mathbb{Z}_{\geq 0}, k_i = 0 \text{ otherwise}$$

is optimal since

$$\left(1 + \frac{2^n - 1}{3}\right) - \left(1 + \frac{2^n - 2}{3}\right) = \frac{1}{3}.$$

□

For  $n$  even the lower bound of Theorem 3.1 is sharp. It is easily seen that the function  $F(x) = x^3$  has image size  $|V_F| = \frac{2^n+2}{3}$  and preimage size distribution  $k_1 = 1$ ,  $k_2 = 0$ ,  $k_3 = \frac{2^n-1}{3}$  and  $k_i = 0$  for  $i > 3$ .

For the case  $n$  odd the given bound is not sharp as we will show later in Proposition 3.3. But we are able to give the following example which is quite close to the lower bound at least for small dimensions. We present an alternative proof for its preimage size distribution in comparison to the one given in [8].

**Example 3.2** ([8]). *Let  $F: \mathbb{F}_{2^n} \rightarrow \mathbb{F}_{2^n}$  be a function given by  $x \mapsto x^4 + x^3$ . If  $n$  is odd then*

$$|V_F| = 2^{n-1}$$

*with preimage size distribution  $k_1 = 0$ ,  $k_2 = 2^{n-1}$  and  $k_i = 0$  for  $i > 2$ .*

*Proof.* It is sufficient to show that for  $c \in \mathbb{F}_{2^n}$  the equation

$$x^4 + x^3 + c = 0 \tag{4}$$

has either no solution or two solutions. For  $c = 0$  it follows directly that 0 and 1 are the solutions of (4). So let  $c \neq 0$  and  $\alpha \in \mathbb{F}_{2^n} \setminus \{0, 1\}$  be a solution of (4). Setting  $x = z + (\alpha + 1)$  it remains to observe the equation

$$\frac{x^4 + x^3 + c}{x + \alpha} = z^3 + (\alpha + 1)z + \alpha(\alpha + 1) = 0. \tag{5}$$

Let  $\text{Tr}: \mathbb{F}_{2^n} \rightarrow \mathbb{F}_{2^n}$  be the *trace* function over  $\mathbb{F}_{2^n}$ , e.g

$$\text{Tr}: \mathbb{F}_{2^n} \rightarrow \mathbb{F}_{2^n} : x \mapsto x + x^2 + \dots + x^{2^{n-1}}.$$

By Theorem 1 of [13] and by

$$\text{Tr}\left(\frac{(\alpha + 1)^3}{(\alpha(\alpha + 1))^2}\right) = \text{Tr}(\alpha^{-2}(\alpha + 1)) = \alpha^{-1} + \alpha^{-2^n} = 0$$

it follows now that (5) has exactly one solution and therefore (4) exactly two solutions. □

Next proposition shows that for  $n = 3$  the discussed Example 3.2 provides the best possible bound and for  $n = 5$  it is almost best possible.

**Proposition 3.3.** *Let  $F: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  be an APN function.*

(a) *For  $n = 3$  it follows  $|V_F| \geq 2^2 = 4$ .*

(b) *For  $n = 5$  it follows  $|V_F| \geq 2^4 - 1 = 15$ .*

*Both lower bounds are sharp.*

*Proof.* (a): By Theorem 3.1 it follows that  $|F(\mathbb{F}_2^3)| \geq 3$ . Assume that  $|F(\mathbb{F}_2^3)| = 3$ . The only possible preimage size distribution is  $k_1 = 0$ ,  $k_2 = 1$ ,  $k_3 = 2$  and  $k_i = 0$  for  $i > 3$ , which follows easily from (1) and (2). So, fix  $F(\mathbb{F}_2^3) = \{y_1, y_2, y_3\}$  with  $|F^{-1}(y_1)| = |F^{-1}(y_2)| = 3$ ,  $|F^{-1}(y_3)| = 2$ . Without loss of generality we can assume  $F^{-1}(y_1) = \{0, x_1, x_2\}$  with different  $x_1, x_2 \in \mathbb{F}_2^3 \setminus \{0\}$  and therefore  $S_2(F^{-1}(y_1)) = \{x_1, x_2, x_1 + x_2\}$ . Let  $x_3 \in \mathbb{F}_2^3$  be such that  $x_1, x_2, x_3$  are linearly independent. Then  $F^{-1}(y_2) = \{x_3, x_1 + x_2\}$  is the only possible set with more than one element such that  $S_2(F^{-1}(y_1)) \cup S_2(F^{-1}(y_2)) = \emptyset$ . But this contradicts  $|F^{-1}(y_1)| = 3$  and therefore  $|F(\mathbb{F}_2^3)| \geq 4$ . Example 3.2 attains this bound.

(b): Computer based. □

The result of Proposition 3.3(b) was found with extensive computations made with a program written in C++. Let  $G: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  be an APN function representing an EA equivalence class. It is sufficient to calculate the size of the value set and preimage size distribution of all  $F = G + L$  with  $L: \mathbb{F}_2^n \rightarrow \mathbb{F}_2^n$  linear to find the minimal size of the value set and all its preimage size distributions from the whole EA equivalence class.

For  $n = 5$  there exist 7 EA equivalence classes of APN functions as shown in [2]. Our computational results about the minimal size of a value set and the preimage size distributions are listed in Table 1. It is notable that apart from some functions with value set of minimal size and EA equivalent to the inverse function every other APN function with value set of minimal size has the same preimage size distribution  $k_1 = 0$ ,  $k_2 = 14$ ,  $k_3 = 0$ ,  $k_4 = 1$  and  $k_i = 0$  for  $i > 4$ .

Even for  $n = 7$  the complexity of finding APN functions with value sets of minimal size of one EA equivalence class with the given algorithm is exploding.

Table 1: APN functions for  $n = 5$  with minimal value set size up to EA equivalence and preimage size distribution  $(k_i)_{1 \leq i \leq 32}$  (we have  $k_i = 0$  for  $i > 5$ ).

#	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	6	11	31	16	8	20	30	4	20	23	21	24	22	4	24

2	0	2	13	9	13	27	25	9	16	8	25	7	10	6	26	16
3	0	10	4	15	10	2	10	3	3	13	15	0	25	21	16	29
4	0	6	31	24	29	25	6	3	20	22	3	0	25	25	11	10
5a	0	17	17	27	8	20	17	4	4	2	18	25	21	21	28	15
5b	0	27	7	7	8	30	7	24	31	19	31	30	14	4	17	8
5c	0	10	28	13	2	5	22	24	29	0	6	22	6	29	2	10
5d	0	0	11	16	23	26	20	16	27	12	23	13	21	4	6	4
5e	0	30	24	29	11	24	27	1	0	9	31	27	18	29	18	14
5f	0	5	5	27	9	1	4	5	4	22	6	25	20	0	9	14
5g	0	2	7	30	21	26	26	28	30	11	30	6	18	1	13	13
5h	0	3	7	31	18	28	29	26	22	2	22	15	29	15	2	3
5i	0	23	29	17	6	28	19	0	17	17	11	6	14	8	11	30
6	0	17	25	18	20	9	22	4	16	24	31	31	16	17	24	4
7	0	28	9	16	29	16	4	19	4	30	15	28	22	9	27	18

#	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1	23	13	30	22	0	4	6	16	4	8	21	11	31	13	1	1
2	2	10	0	14	6	26	29	7	14	28	8	28	29	27	2	2
3	25	27	13	14	22	22	4	5	29	27	5	2	10	14	21	16
4	5	11	10	5	29	17	20	25	27	17	24	19	27	19	31	22
5a	14	28	22	8	20	21	11	22	14	20	2	22	4	0	25	15
5b	0	24	14	26	26	17	19	4	27	11	1	31	17	31	26	6
5c	4	13	17	20	20	14	6	0	29	28	28	19	29	2	13	0
5d	25	26	27	20	28	12	25	21	6	13	16	21	19	6	20	19
5e	15	18	30	15	22	24	0	18	11	30	14	21	2	9	22	15
5f	2	4	14	4	25	12	18	27	2	12	26	26	9	25	0	2
5g	0	1	14	3	7	21	14	0	26	19	0	7	13	26	6	3
5h	20	20	26	22	20	7	29	18	6	14	28	26	22	0	29	25
5i	2	22	22	14	22	17	5	30	23	11	23	5	19	17	2	18
6	25	10	10	18	0	20	16	26	26	22	5	16	7	9	7	5
7	29	26	19	27	26	17	10	17	0	18	30	15	0	10	22	0

#	$ F(\mathbb{F}_2^5) $	$k_1$	$k_2$	$k_3$	$k_4$	$k_5$	$L(x)$	EA
1	15	0	14	0	1	0	$6x^8 + x^{16}$	$x^5$
2	15	0	14	0	1	0	$2x^4 + x^{16}$	$x^3$
3	15	0	14	0	1	0	$9x + 28x^2 + 23x^4 + 17x^8 + 25x^{16}$	[3]
4	15	0	14	0	1	0	$24x + 10x^2 + 7x^4 + 11x^8 + 24x^{16}$	[3]
5a	15	3	7	5	0	0	$28x + 15x^2 + 2x^4 + x^8$	$x^{15}$
5b	15	3	8	3	1	0	$22x + 11x^2 + 6x^4 + x^8$	$x^{15}$
5c	15	6	3	4	2	0	$8x + 10x^2 + 9x^4 + x^8 + x^{16}$	$x^{15}$
5d	15	2	9	4	0	0	$25x + 18x^2 + 9x^4 + 2x^8 + x^{16}$	$x^{15}$
5e	15	4	6	4	1	0	$15x + 13x^2 + 30x^4 + 2x^8 + x^{16}$	$x^{15}$
5f	15	5	4	5	1	0	$16x + 17x^2 + 12x^4 + 8x^8 + x^{16}$	$x^{15}$
5g	15	5	5	3	2	0	$6x + 11x^2 + 7x^4 + 8x^8 + x^{16}$	$x^{15}$
5h	15	4	7	2	2	0	$16x + 28x^2 + 2x^4 + 13x^8 + x^{16}$	$x^{15}$
5i	15	4	7	3	0	1	$21x + 16x^2 + 20x^4 + 6x^8 + x^{16}$	$x^{15}$
6	15	0	14	0	1	0	$27x + 2x^2 + 8x^4 + x^{16}$	$x^{11}$

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7      15      0    14    0    1    0     $11x + 30x^2 + 9x^4 + x^{16}$        $x^7$

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## 4 Conclusion

In this paper we gave a lower bound for the size of the value set of an APN function in explicit form and proof it with methods of linear programming.

However it is only sharp for even dimensions. Hence further work has to be done to sharpen the lower bound for higher odd dimensions. Of course, a characterisation of all functions attaining the lower bound is also from great interest.

Additionally it would be interesting to find other similar problems which could be solved using methods of linear programming.

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