

Aging of asymmetric dynamics on the random energy model

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Abstract We show aging of Glauber-type dynamics on the random energy model, in the sense that we obtain the annealed scaling limits of the clock process and of the age process. The latter encodes the Gibbs weight of the configuration occupied by the dynamics. Both limits are expressed in terms of stable subordinators.

Keywords Random energy model · Spin glasses · Aging · Age process

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1 Introduction

Out of equilibrium statistical mechanics is notoriously so diverse (as, say, non-elephant biology is) that a general theory is hardly conceivable. Nevertheless, and although it might seem like a paradox at first sight, physicists in the 1990s suggested that the dynamical properties of disordered statistical mechanical systems (spin glasses) should be governed by a common general scheme now known under the name of *aging*.

From a mathematical perspective, at least as a first approximation, proving “aging” basically boils down to showing that a certain additive functional of a (family of) Markov chain(s) scales to a stable subordinator. In spite of the universality of the aging phenomenon claimed by physicists, until this paper, only one specific dynamics, called RHT, could be rigorously handled. Thus, as pointed out in their conclusion by the authors of [6], “Even in the case of the REM, we do not know at this point how to deal with different, and more usual, dynamics [...] This problem remains one of the great challenges in the field.”

It is the aim of the present paper to tackle the challenge, and show that the aging picture is actually valid for a large class of dynamics on the REM.

The random energy model (REM) was introduced in [22, 23] as a simple model of a spin glass. It is a mean-field model living on the hypercube $V_N = \{0, 1\}^N$, and the energies (E_x) associated with each configuration $x \in V_N$ are taken to be i.i.d. random variables. We assume that they are distributed as the positive part of a standard Gaussian random variable. The Gibbs weights of the model are thus of the form

$$\tau_{N,x} = e^{\beta\sqrt{N}E_x}, \quad (1.1)$$

where $\beta > 0$ is the inverse temperature.

Unlike other spin glass models where the energies display some complicated correlation, as for instance the SK model, the statics of the REM may be described in detail using results on the extremes of families of independent Gaussian random variables [29, 38]. Roughly speaking, the energy landscape of the REM may be thought of as consisting of a bulk of configurations of energies of order 1, with a few scattered deep wells where $\sqrt{N}E_x$ is of order cN for some constant c . These deep wells carry most of the weight of the Gibbs measure (for a constant c which actually depends on β).

The simple structure of the energies in the REM also made it possible to study its relaxation to equilibrium under a Metropolis or Glauber dynamics. Asymptotics of the spectral gap are known [24]. We refer to [35] and [36] for further results on thermalization times.

It is believed that, for a large class of reversible dynamics, the off-equilibrium dynamics observed before thermalization should be described using the language of

aging. A crude picture of the phenomenon of aging goes as follows: on well-chosen time and depth scales, the dynamics should spend most of its time in a few deep wells. Before it reaches equilibrium, one may think that the dynamics is transient: it finds a deep well, spends some amount of time around it and then moves through the bulk to a second well, and so on, without ever returning to a previously visited well. In such a scenario, at a given time t , the dynamics is with high probability in a deep well whose depth is of order t . Thus one can evaluate the “age” of the dynamics from the value of the energy of the current configuration.

One way to quantify this aging phenomenon is by computing correlation functions. One may for instance try to derive asymptotics of the probability that the dynamics stays in a small region of its state space between times t and $t + s$. From the discussion above, it follows that a reasonable choice is to take s proportional to t . As we expect the main contribution to such a correlation function to arise from deep wells, and since the statistics of extremes of exponentials of Gaussian fields are given by Poisson point processes with polynomial tails, it is natural to believe that asymptotics of correlation functions should be related to stable subordinators. More precisely, back-of-the-envelope computations show that correlation functions should follow the arc-sine law.

More recently, a different and more ambitious description of aging has been proposed that, instead of correlation functions, focuses on deriving the scaling limit of what we call the *age process*. This process gives, at any time, the value of the Gibbs weight of the configuration occupied by the dynamics. Once again, it is easy to guess how these should be related to stable subordinators. In the transient regime we are considering now, the scaling limit of the age process should be universal and given by the jumps of a stable subordinator computed at the inverse of a (different and correlated) subordinator, as in [28].

Although this description of the dynamics may seem simple, proving that it is correct turned out to be a mathematically difficult problem. As far as the REM is concerned, so far, rigorous results had only been obtained for one specific dynamics called the *random hopping times* (RHT) dynamics. It is the aim of the present paper to go beyond this limitation.

In the RHT dynamics, the process stays at a given configuration an exponentially distributed time whose parameter is the inverse of its Gibbs weight, and then jumps to any neighbouring configuration with uniform probability. In other words, in the RHT dynamics, one spin flips at a time, and the spin that flips is chosen uniformly at random among the N possibilities, independently of the past, independently of the current configuration and independently of the energy landscape. This feature implies that the trajectory (i.e. the sequence of successively visited configurations) follows the same law as the trajectory of a simple random walk on V_N : the only way the energies enter in the dynamics is through the holding times. In other words, the RHT dynamics is a time-changed simple random walk on V_N , and this simplifies the mathematical analysis a lot. The time change itself is usually called the *clock process*. To be coherent with our description of aging, one conjectures that this clock process converges to a stable subordinator.

Rigorous results on the RHT dynamics for the REM focused on proving the convergence of correlation functions to the arc-sine law, see [8,9,11,30].

The aim of our paper is to prove that the aging picture holds for Glauber-type local dynamics in which the law of the jumps depends on the energies of both the current and the target configurations. We obtain the scaling limit of the corresponding clock process (a stable subordinator, as expected) and show that the scaling limit of the age process is the same as in [28].

When moving from RHT dynamics to Glauber dynamics, new difficulties appear. Some of these are due to the fact that the potential theory of a symmetric Markov chain on the hypercube is more involved in the generic case than in the simple symmetric case. Also, for the RHT dynamics, the distribution of the energy landscape around (but excluding), say, the first deep trap visited, is simply the Gibbs measure. This is no longer the case for a Glauber dynamics, and the crux is to understand this distribution.

Let us summarize our strategy of proof in a few words. We view the dynamics as a time-change of another process, which is the original dynamics accelerated by a factor $\tau_{N,x}$ at every site $x \in V_N$. Although this new process is no longer a simple random walk as for the RHT dynamics, it retains some of its properties, as for instance the reversibility with respect to the uniform measure over V_N . We prove a law of large numbers for the number of sites discovered by this walk: on appropriate time scales, we show that this number grows asymptotically linearly with time, with a proportionality constant depending neither on the trajectory, nor on the environment.

Our second major step is to identify how the environment around a deep trap found by the dynamics is distributed. Roughly speaking, we follow an idea of [37] and show that asymptotically, this distribution has an explicit density with respect to the product measure, given in terms of a Green function. Care must be taken in order to make this statement precise, since the underlying graph changes with N . As opposed to [37], we must thus resort to a *finitary* version of asymptotic convergence, in the sense that we only write statements for finite N with explicit bounds, instead of statements about limit distributions.

In order to complete the description of the distribution of the environment around a deep trap, we must then study the asymptotic behaviour of the Green function under the product measure. This can be performed via explicit computations, provided that the dynamics we study is not too predictable.

From the law of large numbers and the knowledge of the Green function at a deep trap, we finally derive the joint asymptotic behaviour of all the relevant quantities associated with the visits of traps: the time until the n th deep trap is met, the depth of the trap, and the total time spent on it. The aging picture then follows by noticing that the time spent outside of deep traps is negligible.

Many aspects of this approach do not depend too much on the choice of the dynamics, but the step of the proof we just described concerning the precise description of the Green function seems to be very model-dependent. Here we choose to deal with a Bouchaud dynamics with so-called asymmetry parameter a_N satisfying assumption (2.2) (see the related discussion there). Other choices are possible which would lead to new difficulties.

We close this introduction by a short discussion on related issues that are not directly addressed here.

There exists another spin-glass toy model on which a rather complete description of the dynamics can be easily obtained, namely the REM on the complete graph. In

the RHT dynamics on the complete graph, when jumping, the dynamics chooses to go to any of the 2^N possible configurations with equal probability. Aging results (in the sense of convergence of correlation functions to the arc-sine law) have been obtained in this case [10, 15–17]. For this model on the complete graph, it turns out to be also possible to consider a certain class of Glauber-type dynamics called the asymmetric dynamics, and prove aging for these with renewal techniques [31]. The definition of asymmetric dynamics is similar to the dynamics we consider here. Observe however that the asymmetric dynamics on the complete graph (and only on the complete graph!) has a very special structure: at a jump time, it chooses where to go according to a law that depends on the energies (which is reasonable) but that does not depend on the current configuration (which is less reasonable). As a consequence, the clock process is a subordinator already in finite volume, a fact that helps to prove it converges to a stable subordinator.

Limit theorems for the RHT dynamics on the p -spin model are discussed in [7, 18].

The aging picture we described above has also been investigated on models that are not related to spin glass theory. These are often referred to in the literature as *trap models*: one starts with a discrete-time Markov chain on a graph, which may be finite or infinite, and considers its time change through an additive functional as in the RHT dynamics, looking for scaling limits of either the correlation functions or the age process. We refer to [11] for results in this direction. In particular, models of non-simple random walks on \mathbb{Z}^d ($d \geq 2$) with aging properties have been considered in [4, 20, 32, 37].

So far we only discussed dynamics in the transient regime, long before thermalization occurs. For dynamical spin glasses, as for more general trap models on a growing sequence of graphs, it makes sense to look for scaling limits on the ergodic time scale as well. The first results in that direction dealt with the RHT dynamics on the complete graph [27]. The scaling limits that appear are known as K -processes. These interpolate between the transient regime, for small times, and the usual thermalization regime. It was later proved that K -processes describe the RHT dynamics in the REM [25] or the a -symmetric dynamics on the complete graph [13]. More recently, [34] showed how K -processes arise as a universal limit for trap models on growing sequences of graphs.

On the other side, it is also possible to derive aging results for dynamics of spin glass models on very short time scales. This is often referred to as *extreme aging*, see [12, 19].

The paper is organized as follows. In Sect. 2, we introduce basic definitions and notation. We then provide various quantitative estimates on the mixing properties of the accelerated walk in Sect. 3. Section 4 introduces the notion of the exploration process. The law of large numbers for the number of sites discovered by the walk is then achieved in Sect. 5. Next, Sect. 6 defines the relevant scales of our problem, in particular that of the deep traps. In Sect. 7, we obtain the joint scaling limit of the time it takes to find a deep trap, and of the depth of the deep trap. After recalling elementary properties of the process of the environment viewed by the particle in Sect. 8, we tackle the problem of controlling the distribution of the environment around the first deep trap met in Sect. 9. Section 10 is devoted to the asymptotic analysis of the Green function under the product measure. Combining the two previous sections, we obtain

the scaling limit of the Green function at the first deep trap met in Sect. 11. We then derive the joint convergence of all the relevant quantities associated with the visits of the traps in Sect. 12. We conclude by deducing the convergence of the clock process and of the age process, in Sects. 13 and 14 respectively.

2 Definitions and notation

We view the hypercube $V_N = \{0, 1\}^N$ as an additive group, endowed with its usual graph structure (that is, nearest-neighbour for the Hamming distance, that we write $|\cdot|$). For $x, y \in V_N$, we write $x \sim y$ when $|x - y| = 1$. Let $(E_x)_{x \in V_N}$ be i.i.d. random variables distributed as the positive part of a standard Gaussian. We write \mathbb{P} for their joint law (with associated expectation \mathbb{E}), and $\mathcal{N}_+(0, 1)$ for the marginal distribution. Recall that $\beta > 0$ is a fixed parameter, and that $\tau_{N,x} = e^{\beta\sqrt{N}E_x}$. We write $\tau_N = (\tau_{N,x})_{x \in V_N}$.

For $a_N \in \mathbb{R}$, we consider the continuous-time Markov chain $(Z_t)_{t \geq 0}$ whose jump rate from x to a neighbour y is given by

$$\frac{e^{a_N(E_x + E_y)}}{e^{\beta\sqrt{N}E_x}}, \tag{2.1}$$

and write $\mathbf{P}_z^{\tau_N}$ for the law of this chain started from $z \in V_N$ (and $\mathbf{E}_z^{\tau_N}$ for the associated expectation). This dynamics, often called *Bouchaud's dynamics*, is reversible for the measure with weights $(\tau_{N,x})_{x \in V_N}$. The case $a_N = 0$ makes the jump rate in (2.1) independent of y , and thus corresponds to the RHT dynamics. It is physically natural to consider dynamics that are more attracted to sites whose associated Gibbs weight is high, so we will only consider the case $a_N \geq 0$. For technical reasons, it is convenient to assume from now on that actually $a_N \geq 1$.

If $a_N \gg \sqrt{\log N}$, then with probability tending to 1, the walk started from the origin will make its first jump to the neighbouring site of highest energy. This asymptotic complete predictability persists for subsequent jumps, in the sense that for every k , one can predict with probability tending to 1 the sequence of the first k distinct sites that will be visited by the dynamics. In order to avoid such a behaviour, we will assume instead that

$$a_N \leq \bar{a}\sqrt{2 \log N}, \tag{2.2}$$

and moreover, that $\bar{a} < 1/20$. It is instructive to figure out the large N behaviour of the extreme values of the jump rates from the origin to each of its neighbours in this case. Up to a multiplicative factor, this amounts to understanding the extreme values of the family $(e^{a_N E_y})_{y \sim 0}$. By the classical theory of extremes for independent Gaussian random variables, when the constraint (2.2) is replaced by an equality, the point process of the rescaled $(e^{a_N E_y})_{y \sim 0}$ converges to the point process with intensity measure $x^{-(1+1/\bar{a})} dx$. In particular, the jump rates remain inhomogeneous even in the large N limit.

Assumption (2.2) will be used in order to prove that when a walk moves at some fixed distance away from a deep trap, it will not manage to find it back rapidly. The parameter $1/20$ is chosen for convenience. The proof below can be optimized to cover higher values of \bar{a} , but a more detailed analysis would be required to cover every $\bar{a} < 1$ for instance (see Sect. 10).

We rewrite Z as a time-change of a “nicer” random walk. Denote by $(X_t)_{t \geq 0}$ the walk speeded up by τ_x at each x , whose jump rates are thus

$$\omega_N(x, y) = e^{a_N(E_x + E_y)} \quad (x \sim y \in V_N). \tag{2.3}$$

Note that these jump rates are symmetric: $\omega_N(x, y) = \omega_N(y, x)$. In other words, the uniform measure is reversible for this process. We will denote the uniform probability measure over V_N by u_N , and write $\mathbf{P}_u^{\tau_N} = \mathbf{P}_{u_N}^{\tau_N}$ for simplicity. We write $\bar{\mathbb{P}}_N$ for $\mathbb{P}_{u_N}^{\tau_N}$,

$$\omega_N(x) = e^{a_N E_x} \sum_{z \sim x} e^{a_N E_z}, \tag{2.4}$$

and $\bar{\omega}_N = \sup_{x \in V_N} \omega_N(x)$.

We also define

$$\phi(\lambda) = \mathbb{E} \left[e^{\lambda E_x} \right] = \frac{1}{2} + \frac{e^{\lambda^2/2}}{\sqrt{2\pi}} \int_{-\lambda}^{+\infty} e^{-u^2/2} du \leq 2e^{\lambda^2/2}. \tag{2.5}$$

General notation If A is a set, $|A|$ denotes its cardinality. We write $\mathbb{N} = \{1, 2, \dots\}$, and $a \wedge b = \min(a, b)$. For two sequences u_N, v_N with $v_N \neq 0$ for all sufficiently large N , we write $u_N \sim v_N$ if u_N/v_N tends to 1 as N tends to infinity. In the spirit of the Bachmann–Landau “big O” notation, for $\varepsilon > 0$, we write $\pm\varepsilon$ to denote any real number whose value lies in $[-\varepsilon, \varepsilon]$ (this notation is convenient when we want to make explicit the fact that an estimate holds uniformly in other parameters).

3 Mixing properties

In this section, we provide various precise versions of the idea that the random walk X has good mixing properties. In the first proposition, we show that the walk started from any fixed point in V_N admits strong stationary times of order N . In particular, the walk at the strong stationary time is distributed as u_N (the uniform measure on V_N), and the time scale of order N is very small compared to the exponentially growing time scales of our problem. The purpose of Propositions 3.4 and 3.5 is slightly different, since we will use them to show that the random walk has very little probability to be at a specific location after some time. Proposition 3.4 says that for almost every environment, it suffices to wait a time $t \gg 1$ for the walk to “get lost”. Proposition 3.5 requires only $t \gg 1/N$, but the result is averaged over the environment.

The definition of strong stationary times requires that the probability space contains additional independent randomness. Possibly enlarging the probability space,

we assume that there exists infinitely many independent random variables distributed uniformly on $[0, 1]$ and independent of everything else. Following [2], we say that a random variable $T \geq 0$ is a *randomized stopping time* if the event $\{T \leq t\}$ depends only on $\{X_s, s \leq t\}$ and on the value of these additional random variables.

Proposition 3.1 *For any N large enough and any τ_N , there exists a randomized stopping time T_N with values in $\{N, 2N, \dots\}$ such that for any $x \in V_N$, under $\mathbf{P}_x^{\tau_N}$,*

- (1) *the distribution of X_{T_N} is u_N ,*
- (2) *for any $k \in \mathbb{N}$,*

$$\mathbf{P}_x^{\tau_N} [T_N \geq kN] = e^{-(k-1)},$$

- (3) *T_N and X_{T_N} are independent random variables.*

Remark 3.2 A (randomized) stopping time satisfying (1) is called a *stationary time*; one satisfying (1) and (3) a *strong stationary time*.

Remark 3.3 Note in particular that the distribution of (T_N, X_{T_N}) does not depend on the environment τ_N .

Proof Since the jump rates of X are symmetric, the measure u_N is reversible for this walk. Let

$$\mathcal{E}_N(f, f) = \frac{1}{2^{N+1}} \sum_{x \sim y} (f(x) - f(y))^2 e^{a_N(E_x + E_y)},$$

where $x \sim y$ means that x and y are neighbours in V_N . For a given realization of the E_x 's, the bilinear form \mathcal{E}_N acting on $L_2(V_N, u_N)$ is the Dirichlet form of the process X . We similarly introduce

$$\mathcal{E}_N^\circ(f, f) = \frac{1}{2^{N+1}} \sum_{x \sim y} (f(x) - f(y))^2,$$

which defines the Dirichlet form of the Markov chain jumping along the edges of V_N with constant rate 1. We denote this Markov chain by $(X_t^\circ)_{t \geq 0}$.

Observe that

$$\mathcal{E}_N^\circ(f, f) \leq \mathcal{E}_N(f, f). \tag{3.1}$$

Let

$$\text{SG}_N = \inf \left\{ \frac{\mathcal{E}_N(f, f)}{u_N [(f - u_N(f))^2]}, f : V_N \rightarrow \mathbb{R} \text{ non constant} \right\}$$

be the spectral gap associated with the Dirichlet form \mathcal{E}_N on $L_2(V_N, u_N)$, and let

$$\mathbf{SG}_N^\circ = \inf \left\{ \frac{\mathcal{E}_N^\circ(f, f)}{u_N [(f - u_N(f))^2]}, f : V_N \rightarrow \mathbb{R} \text{ non constant} \right\}$$

be the spectral gap of \mathcal{E}_N° .

On the one hand, inequality (3.1) implies that $\mathbf{SG}_N^\circ \leq \mathbf{SG}_N$. On the other hand, X° is simply the N -fold product of the simple random walk on V_1 , so by [33, Theorem 2.5], we have $\mathbf{SG}_N^\circ = \mathbf{SG}_1^\circ$, and in fact $\mathbf{SG}_1^\circ = 2$. Therefore

$$\mathbf{SG}_N \geq 2. \tag{3.2}$$

Let us now introduce

$$\begin{aligned} s_{\text{ST}}(\tau_N, t) &= \min \{s \geq 0 : \forall x, y \in V_N, \mathbf{P}_x^{\tau_N} [X_t = y] \geq (1 - s)u_N(y)\}, \\ \bar{d}(\tau_N, t) &= \max_{x, y \in V_N} \left\| \mathbf{P}_x^{\tau_N} [X_t \in \cdot] - \mathbf{P}_y^{\tau_N} [X_t \in \cdot] \right\|_{\text{TV}}, \end{aligned}$$

where $\|\cdot\|_{\text{TV}}$ denotes the total variation distance, and

$$\mathcal{T}_N = \inf \{t \geq 0 : \bar{d}(\tau_N, t) \leq e^{-1}\}.$$

We learn from [1, Lemmas 5, 7 and 23 of Chapter 4] that, respectively,

$$\begin{aligned} \bar{d}(\tau_N, t) &\leq e^{-\lfloor t/\mathcal{T}_N \rfloor}, \\ s_{\text{ST}}(\tau_N, 2t) &\leq 1 - (1 - \bar{d}(\tau_N, t))^2, \\ \mathcal{T}_N &\leq \frac{1}{\mathbf{SG}_N} \left(1 + \frac{1}{2} \log \frac{1}{u_N^*} \right), \end{aligned}$$

where $u_N^* = \min_x u_N(x)$, which in our case is 2^{-N} . Using (3.2), we thus derive from these three observations that, for N large enough and any τ_N ,

$$s_{\text{ST}}(\tau_N, N) \leq e^{-1},$$

that is, for any $x, y \in V_N$ and any τ_N ,

$$\mathbf{P}_x^{\tau_N} [X_N = y] \geq (1 - e^{-1})u_N(y).$$

Following [3, Proposition (3.2)], we can thus define the strong stationary time \mathbb{T}_N , with values in $\{N, 2N, \dots\}$. Let (U_1, U_2, \dots) be independent random variables distributed uniformly on $[0, 1]$, independent of everything else. Conditionally on $X_N = y$, we let $\mathbb{T}_N = N$ if

$$U_1 \leq \frac{(1 - e^{-1})u_N(y)}{\mathbf{P}_x^{\tau_N} [X_N = y]} \quad (\leq 1).$$

Otherwise, we define T_N inductively: for every $k \in \mathbb{N}$, conditionally on $T_N > kN$, on $X_{kN} = z$ and on $X_{(k+1)N} = y$, we let $T_N = (k + 1)N$ if

$$U_{k+1} \leq \frac{(1 - e^{-1})u_N(y)}{\mathbf{P}_z^{\tau_N}[X_N = y]} \quad (\leq 1).$$

By construction, we have

$$\mathbf{P}_x^{\tau_N}[T_N = N \mid X_N = y] = \frac{(1 - e^{-1})u_N(y)}{\mathbf{P}_x^{\tau_N}[X_N = y]},$$

so that

$$\mathbf{P}_x^{\tau_N}[T_N = N, X_N = y] = (1 - e^{-1})u_N(y).$$

Similarly, we have

$$\mathbf{P}_x^{\tau_N}[T_N = (k + 1)N, X_{(k+1)N} = y \mid T_N > kN, X_{kN} = z] = (1 - e^{-1})u_N(y).$$

By induction on k , we obtain that for any $k \in \mathbb{N}$ and any $x, y \in V_N$,

$$\mathbf{P}_x^{\tau_N}[T_N = kN, X_{kN} = y] = e^{-(k-1)}(1 - e^{-1})u_N(y),$$

and this finishes the proof. □

Proposition 3.4 *For any environment τ_N , any $x, y \in V_N$ and any $t \geq 0$,*

$$\left| \mathbf{P}_x^{\tau_N}[X_t = y] - 2^{-N} \right| \leq e^{-2t}.$$

Proof The proposition is a direct consequence of [39, Corollary 2.1.5] and the spectral gap estimate (3.2). □

Proposition 3.5 *For any $x \in V_N$ and any $t \geq 0$,*

$$\mathbb{P}\mathbf{P}_x^{\tau_N}[X_t = x] \leq \left(\frac{1 + e^{-2t}}{2} \right)^N.$$

Proof We recall that $(X_t^\circ)_{t \geq 0}$ is the Markov chain whose jump rate from one point to any of its neighbours is equal to 1. Since these jump rates are dominated by the jump rates of (X_t) , and using [26, Lemma 2.2], we get that

$$\mathbb{P}\mathbf{P}_x^{\tau_N}[X_t = x] \leq \mathbb{P}\mathbf{P}_x^{\tau_N}[X_t^\circ = x].$$

Each coordinate of (X_t°) is a Markov chain on two states with jump rate equal to 1 from one state to the other, and that evolves independently of the other coordinates. This leads to the announced result. □

Remark 3.6 As is well-known, such on-diagonal upper bound on the heat kernel automatically transfers to off-diagonal decay. In other words, for any $x, y \in V_N$,

$$\mathbb{P}\mathbf{P}_x^{\tau_N}[X_t = y] \leq \left(\frac{1 + e^{-2t}}{2}\right)^N. \tag{3.3}$$

To see this, note that

$$\mathbf{P}_x^{\tau_N}[X_t = y] = \sum_z \mathbf{P}_x^{\tau_N}[X_{t/2} = z] \mathbf{P}_z^{\tau_N}[X_{t/2} = y],$$

which by the Cauchy–Schwarz inequality, is smaller than

$$\left(\sum_z \mathbf{P}_x^{\tau_N}[X_{t/2} = z]^2\right)^{1/2} \left(\sum_z \mathbf{P}_z^{\tau_N}[X_{t/2} = y]^2\right)^{1/2}.$$

By reversibility, the first sum above is equal to

$$\sum_z \mathbf{P}_x^{\tau_N}[X_{t/2} = z] \mathbf{P}_z^{\tau_N}[X_{t/2} = x] = \mathbf{P}_x^{\tau_N}[X_t = x],$$

and we arrive at

$$\mathbf{P}_x^{\tau_N}[X_t = y] \leq \mathbf{P}_x^{\tau_N}[X_t = x]^{1/2} \mathbf{P}_y^{\tau_N}[X_t = y]^{1/2}.$$

After integrating with respect to \mathbb{P} , we use the Cauchy–Schwarz inequality again and Proposition 3.5 to obtain (3.3).

4 The exploration process

In this section, we define an enumeration of V_N along the trajectory of the random walk X , as follows. Since the walk eventually visits every site of V_N , we can let Y_1, \dots, Y_{2N} be the sequence of successive sites visited by X . Consider the sequence of sites

$$\mathcal{S} = (Y_1 + z)_{|z| \leq 1}, \dots, (Y_{2N} + z)_{|z| \leq 1},$$

where $(\cdot + z)_{|z| \leq 1}$ is enumerated in some arbitrary order. Clearly, \mathcal{S} spans V_N . We let

$$\mathcal{S}' = x_1, x_2, \dots, x_{2N} \tag{4.1}$$

be the sequence \mathcal{S} with repetitions removed (in other words, for every $x \in V_N$, the first occurrence of x in \mathcal{S} is kept, and all subsequent occurrences are deleted). The sequence \mathcal{S}' spans V_N by construction, and we refer to this sequence as the *exploration process*.

Let $x \in V_N$. The distribution of the trajectory up to the time when the walk is within distance 1 from x is independent of E_x . From this observation, we can derive the following result (see [37, Proposition 4.1] for a complete proof).

Proposition 4.1 *For any $z \in V_N$, under the measure $\mathbb{P}\mathbb{P}_z^{t_N}$, the random variables $(E_{x_n})_{1 \leq n \leq 2^N}$ are independent and follow a $\mathcal{N}_+(0, 1)$ distribution. This holds also under the measure \mathbb{P}_N .*

5 Law of large numbers for the number of discovered sites

For every $t \geq 0$, let

$$\begin{aligned} \mathcal{D}_N(t) &= \{x \in V_N : \exists s \leq t \text{ s.t. } |X_s - x| \leq 1\}, \\ \mathcal{R}_N(t) &= \{x \in V_N : \exists s \leq t \text{ s.t. } X_s = x\}, \end{aligned}$$

and $D_N(t) = |\mathcal{D}_N(t)|$, $R_N(t) = |\mathcal{R}_N(t)|$. We say that a site $x \in V_N$ is *discovered before time t* if it belongs to $\mathcal{D}_N(t)$, and that it is *visited before time t* if it belongs to $\mathcal{R}_N(t)$.

More generally, for a subset $A \subseteq V_N$, we define

$$\mathcal{D}_N^A(t) = \{x \in V_N : \exists s \leq t \text{ s.t. } X_s \in x + A\},$$

and $D_N^A(t) = |\mathcal{D}_N^A(t)|$. Observe that $\mathcal{D}_N^A(t) = \mathcal{D}_N(t)$ when $A = \{z \text{ s.t. } |z| \leq 1\}$ and $\mathcal{D}_N^A(t) = \mathcal{R}_N(t)$ when A is reduced to the identity element in V_N .

The purpose of this section is to prove the following law of large numbers for the number of discovered sites.

Theorem 5.1 *Let $\bar{c} \in (0, \log(2))$ and (t_N) be such that $\log(t_N) \sim \bar{c}N$. Define $\mathbf{d}_N = \mathbb{E}_N[D_N(t_N)]$. For any $t > 0$, we have*

$$\frac{D_N(t\mathbf{d}_N)}{t\mathbf{d}_N} \xrightarrow[N \rightarrow +\infty]{\mathbb{P}_N\text{-prob.}} 1. \tag{5.1}$$

Moreover, $\log(\mathbf{d}_N) \sim \bar{c}N$.

Before starting the proof of this result, we collect some useful bounds on $\bar{\omega}_N = \sup_{x \in V_N} \omega_N(x)$, where we recall that $\omega_N(x)$ was defined in (2.4).

Lemma 5.2 *For every $c > \sqrt{2 \log 2}$, we have*

$$\mathbb{P} \left[\log(\bar{\omega}_N) > 2c a_N \sqrt{N} \right] \xrightarrow[N \rightarrow \infty]{} 0. \tag{5.2}$$

Moreover, for N sufficiently large,

$$\mathbb{P} \left[\log(\bar{\omega}_N) > N^{3/4} \right] \leq e^{-N^{5/4}}. \tag{5.3}$$

Proof In order to prove these results, we will rely on the fact that for $z \geq 1$,

$$\mathbb{P}[E_x > z] \leq e^{-z^2/2}. \tag{5.4}$$

From this, it readily follows that, for every $c > 0$,

$$\begin{aligned} \mathbb{P} \left[\sup_{x \in V_N} E_x > c\sqrt{N} \right] &\leq 2^N \mathbb{P}[E_x > c\sqrt{N}] \\ &\leq 2^N e^{-c^2 N/2}, \end{aligned}$$

which tends to 0 as soon as $c^2 > 2 \log(2)$. On the event

$$\sup_{x \in V_N} E_x \leq c\sqrt{N},$$

we have

$$\bar{\omega}_N \leq N e^{2a_N c \sqrt{N}},$$

so (5.2) is proved.

For the second part, note that

$$\mathbb{P} \left[\sup_{x \in V_N} E_x > N^{2/3} \right] \leq 2^N e^{-N^{4/3}/2}.$$

On the event

$$\sup_{x \in V_N} E_x \leq N^{2/3},$$

we have

$$\bar{\omega}_N \leq N e^{2a_N N^{2/3}}.$$

Since we assume that $a_N \leq \bar{a} \sqrt{2 \log N}$, we obtain (5.3). □

Proof of Theorem 5.1 In a first step of the proof, we shall derive estimates on the mean and variance of $D_N(t)$ for a fixed realization of τ_N . These imply a law of large numbers as in (5.1) but with d_N replaced by $\mathbf{E}_u^{\tau_N} [D_N(t_N)]$ (and therefore depending on τ_N). In a second step, we establish a concentration inequality which allows to replace $\mathbf{E}_u^{\tau_N} [D_N(t_N)]$ by $\bar{\mathbb{E}}_N [D_N(t_N)]$. □

We start by proving that $\log(d_N) \sim \bar{c}N$ and $\log \mathbf{E}_u^{\tau_N} [D_N(t_N)] \sim \bar{c}N$ in \mathbb{P} -probability. It will be a consequence of the following

Lemma 5.3 *We have*

$$\mathbf{E}_u^{\tau_N} [R_N(t)] \leq 3t (1 + \bar{\omega}_N)$$

whenever $t \geq 1$, and

$$\mathbf{E}_u^{\tau_N} [R_N(t)] \geq \frac{t}{2}$$

whenever $t2^{-N} \leq \frac{1}{2}$.

Proof Let us fix a time $t > 0$ and consider an independent exponentially distributed random variable of mean t , say T . Let

$$G_N^t(x, y) = \mathbf{E}_x^{\tau_N} \left[\int_0^{+\infty} e^{-s/t} \mathbf{1}_{X_s=y} ds \right],$$

be the Green function of the process X .

Our estimates rely on the following formula:

$$\mathbf{E}_u^{\tau_N} [R_N(T)] = 2^{-N} \sum_y \frac{t}{G_N^t(y, y)}. \tag{5.5}$$

Indeed it follows from the Markov property that

$$\mathbf{E}_x^{\tau_N} [R_N(T)] = \sum_{y \in V_N} \mathbf{P}_x^{\tau_N} [X \text{ visits } y \text{ before time } T] = \sum_{y \in V_N} \frac{G_N^t(x, y)}{G_N^t(y, y)}.$$

The reversibility of the process X implies that $G_N^t(x, y) = G_N^t(y, x)$. Therefore, summing over x , we get that

$$\mathbf{E}_u^{\tau_N} [R_N(T)] = 2^{-N} \sum_x \sum_y \frac{G_N^t(y, x)}{G_N^t(y, y)}.$$

The equality $\sum_x G_N^t(y, x) = t$ leads to (5.5).

We now explain how to derive an upper bound on $\mathbf{E}_u^{\tau_N} [R_N(T)]$ from (5.5). We assume that $t \geq 1$.

When starting from y , the process X waits for an exponential time of parameter $\omega_N(y) = \sum_{z \sim y} \exp(a_N(E_y + E_z))$ before leaving the point y . Thus we have

$$G_N^t(y, y) \geq \frac{1}{1/t + \omega_N(y)} \geq \frac{1}{1 + \omega_N(y)}.$$

Plugging this estimate in (5.5), we get that

$$\mathbf{E}_u^{\tau_N} [R_N(T)] \leq t2^{-N} \sum_y (1 + \omega_N(y)).$$

One may now replace T by t observing that the function $s \rightarrow \mathbf{E}_u^{\tau_N} [R_N(s)]$ is increasing and therefore

$$\mathbf{E}_u^{\tau_N} [R_N(T)] = \int_0^{+\infty} \mathbf{E}_u^{\tau_N} [R_N(st)] e^{-s} ds \geq \mathbf{E}_u^{\tau_N} [R_N(t)] \int_1^{+\infty} e^{-s} ds.$$

Thus we have established that, for all $t \geq 1$,

$$\mathbf{E}_u^{\tau_N} [R_N(t)] \leq 3t 2^{-N} \sum_y (1 + \omega_N(y)) \leq 3t (1 + \bar{\omega}_N)$$

(we used the inequality $\int_1^{+\infty} e^{-s} ds = e^{-1} \geq 1/3$).

We now turn to lower bounds. We assume that $t2^{-N} \leq \frac{1}{2}$. Integrating the estimate from Proposition 3.4, we get that

$$G_N^t(y, y) \leq t2^{-N} + \frac{t}{1 + 2t} \leq 1.$$

Plugging this estimate in (5.5), we see that one has

$$\mathbf{E}_u^{\tau_N} [R_N(T)] \geq t.$$

One may now replace T by t observing that the function $s \rightarrow \mathbf{E}_u^{\tau_N} [R_N(s)]$ is subadditive and increasing; thus satisfies $\mathbf{E}_u^{\tau_N} [R_N(st)] \leq (s + 1)\mathbf{E}_u^{\tau_N} [R_N(t)]$ and

$$\mathbf{E}_u^{\tau_N} [R_N(T)] \leq \mathbf{E}_u^{\tau_N} [R_N(t)] \int_0^{+\infty} (s + 1)e^{-s} ds.$$

Thus we have established that, for all t such that $t2^{-N} \leq 1/2$,

$$\mathbf{E}_u^{\tau_N} [R_N(t)] \geq \frac{t}{2}.$$

□

Observe from (2.2) and (5.2) that $\frac{1}{N} \log(1 + \bar{\omega}_N)$ converges to 0 in \mathbb{P} -probability.

Thus, if we replace t by t_N , we deduce from the bounds in Lemma 5.3 that $\frac{1}{N} \log \mathbf{E}_u^{\tau_N} [R_N(t_N)]$ converges to \bar{c} in \mathbb{P} -probability. Since $(N + 1) \cdot R_N(t) \geq D_N(t) \geq R_N(t)$, we also conclude that $\frac{1}{N} \log \mathbf{E}_u^{\tau_N} [D_N(t_N)]$ converges to \bar{c} in \mathbb{P} -probability.

Taking the expectation in the bounds in Lemma 5.3 and using (2.5), we also get that

$$\frac{1}{N} \log \bar{\mathbb{E}}_N [D_N(t_N)] \xrightarrow{N \rightarrow +\infty} \bar{c}. \tag{5.6}$$

Now we wish to show that $\mathbf{E}_u^{\tau_N} [D_N(t_N)]^{-1} D_N(t_N)$ converges to 1 in probability. This will follow from the fact that the variance of $D_N(t_N)$ under $\mathbf{P}_u^{\tau_N}$ is negligible compared to the square of its mean.

Lemma 5.4 *For all $p > 0$, there exists a numerical constant $c(p)$ such that*

$$\mathbf{E}_x^{\tau_N} [R_N(t)^p] \leq c(p)(1 + (\bar{\omega}_N t)^p).$$

Proof Let $k \geq 1$. On the event $R_N(t) \geq k + 1$, the process has visited and left some point at least k times. Note that, when at x , the process X waits for an exponential time of parameter $\omega_N(x)$ before leaving the point x . Thus we see that the probability $\mathbf{P}_x^{\tau_N} [R_N(t) \geq k + 1]$ is bounded by the probability that a sum of k i.i.d. exponential(1) random variables is bounded by $\bar{\omega}_N t$. The lemma follows from this observation. \square

We deduce from Lemma 5.4 with $p = 2$ and (5.2) that, for some constant c_2 ,

$$\mathbf{E}_x^{\tau_N} [R_N(t)^2] \leq c(2)(1 + t^2 e^{c_2 a_N \sqrt{N}}), \tag{5.7}$$

with high \mathbb{P} -probability. Since $D_N(t) \leq (N + 1)R_N(t)$, a similar bound holds for $D_N(t)$ with an extra factor $(N + 1)^2$ multiplying $c(2)$.

We also need some control on the self-intersections of the trajectories of the process X . In the next lemma, we consider two Markov chains X and X' that start from the same point in V_N (which will be chosen according to the uniform probability in V_N), and then evolve independently in the same fixed environment τ_N with jump rate from x to y given by $\omega_N(x, y)$ (defined in (2.3)). We define

$$\mathcal{D}_N^A(s) = \{x \in V_N : \exists v \leq s \text{ s.t. } X'_v \in x + A\},$$

$$\text{and } \mathcal{D}_N^A(s, t) = \mathcal{D}_N^A(t) \cap \mathcal{D}_N^A(s), \quad D_N^A(s, t) = |\mathcal{D}_N^A(s, t)|.$$

Lemma 5.5 *Let $s \geq t \geq 1$. We have*

$$\mathbf{E}_u^{\tau_N} [D_N^A(s, t)] \leq 9(2^{-N} s^2 + 1)|A|^2 (1 + \bar{\omega}_N)^2.$$

Proof The strategy is similar to the one we already used in the proof of the upper bound in Lemma 5.3.

Let us fix two times $s \geq t \geq 1$ and consider independent exponentially distributed random variables S and T of mean respectively s and t .

We recall that

$$G_N^t(x, y) = \mathbf{E}_x^{\tau_N} \left[\int_0^{+\infty} e^{-w/t} \mathbf{1}_{X_w=y} dw \right],$$

is the Green function of the process X . Let us also define

$$K_N^t(x, y) = \mathbf{E}_x^{\tau_N} \left[\int_0^{+\infty} e^{-w/t} \mathbf{1}_{X_w=y} w dw \right].$$

We claim that

$$\mathbf{E}_u^{\tau_N} \left[D_N^A(S, T) \right] \leq 2^{-N} \sum_x \sum_{y, y' \in A} \frac{K_N^s(x+y, x+y')}{G_N^t(x+y, x+y) G_N^s(x+y', x+y')}. \tag{5.8}$$

To prove Eq. (5.8), we start by noting that

$$\mathbf{E}_x^{\tau_N} \left[D_N^A(S, T) \right] \leq \sum_z \sum_{y, y' \in A} \frac{G_N^t(x, z+y)}{G_N^t(z+y, z+y)} \frac{G_N^s(x, z+y')}{G_N^s(z+y', z+y')}. \tag{5.9}$$

(This follows from the independence of X and X' and the Markov property: $\frac{G_N^t(x, z+y)}{G_N^t(z+y, z+y)}$ is the probability that X hits $z+y$ before time T . We then use a union bound to control the probability of hitting the set $z+A$ by a sum over $y \in A$.)

From the reversibility, we get that $G_N^t(x, z+y) = G_N^t(z+y, x)$. Observe that

$$\begin{aligned} & \sum_x G_N^t(z+y, x) G_N^s(x, z+y') \\ &= \int_0^{+\infty} du e^{-u/t} \int_0^{+\infty} dv e^{-v/s} \sum_x \mathbf{P}_{z+y}^{\tau_N} [X_u = x] \mathbf{P}_x^{\tau_N} [X_v = z+y'] \\ &= \int_0^{+\infty} du e^{-u/t} \int_0^{+\infty} dv e^{-v/s} \mathbf{P}_{z+y}^{\tau_N} [X_{u+v} = z+y'], \end{aligned}$$

and, since $s \geq t$,

$$\begin{aligned} & \int_0^{+\infty} du e^{-u/t} \int_0^{+\infty} dv e^{-v/s} \mathbf{P}_{z+y}^{\tau_N} [X_{u+v} = z+y'] \\ & \leq \int_0^{+\infty} du e^{-u/s} \int_0^{+\infty} dv e^{-v/s} \mathbf{P}_{z+y}^{\tau_N} [X_{u+v} = z+y'] = K^s(z+y, z+y'), \end{aligned}$$

Summing inequality (5.9) over x , we thus obtain (5.8).

As in the proof of Lemma 5.3, we plug in (5.8) crude estimates on the Green functions. We first recall that, for all z and z' ,

$$G_N^t(z, z) \geq \frac{1}{1/t + \omega_N(z)} \geq \frac{1}{1 + \omega_N(z)},$$

and it follows from Proposition 3.4 that

$$K_N^s(z, z') \leq 2^{-N} s^2 + 1.$$

Thus we derive that

$$\begin{aligned} \mathbf{E}_u^{\tau_N} [D_N^A(S, T)] &\leq (2^{-N} s^2 + 1) \sum_{y, y' \in A} 2^{-N} \sum_x (1 + \omega_N(x + y))(1 + \omega_N(x + y')) \\ &= (2^{-N} s^2 + 1) 2^{-N} \sum_x \left(\sum_{y \in A} (1 + \omega_N(x + y)) \right)^2 \\ &\leq (2^{-N} s^2 + 1) 2^{-N} |A|^2 \sum_x (1 + \omega_N(x))^2 \\ &\leq (2^{-N} s^2 + 1) |A|^2 (1 + \bar{\omega}_N)^2, \end{aligned}$$

where we used the bound $\omega_N(x) \leq \bar{\omega}_N$ in the last inequality.

On the other hand, the function $(s, t) \rightarrow \mathbf{E}_u^{\tau_N} [D_N^A(s, t)]$ being increasing in both arguments, we have $\mathbf{E}_u^{\tau_N} [D_N^A(s, t)] \leq e^2 \mathbf{E}_u^{\tau_N} [D_N^A(S, T)]$.

Putting everything together, we conclude the proof of Lemma 5.5. □

As a consequence of Lemma 5.5, we obtain the linearity of the expected number of discovered sites.

Lemma 5.6 *For all t and s we have*

$$\mathbf{E}_u^{\tau_N} [D_N^A(t)] + \mathbf{E}_u^{\tau_N} [D_N^A(s)] \geq \mathbf{E}_u^{\tau_N} [D_N^A(t + s)],$$

and

$$\mathbf{E}_u^{\tau_N} [D_N^A(t)] + \mathbf{E}_u^{\tau_N} [D_N^A(s)] \leq \mathbf{E}_u^{\tau_N} [D_N^A(t + s)] + \mathbf{E}_u^{\tau_N} [D_N^A(s, t)].$$

Proof The first inequality is obvious.

We define

$$D_N^A(t \rightarrow s) = \{x \in V_N : \exists u \in (t, t + s) \text{ s.t. } X_s \in x + A\} \tag{5.10}$$

to be the set of discovered sites between times t and $t + s$, and $D_N^A(t \rightarrow s) = |\mathcal{D}_N^A(t \rightarrow s)|$.

Note that, by stationarity, we have $\mathbf{E}_u^{\tau_N} [D_N^A(t \rightarrow s)] = \mathbf{E}_u^{\tau_N} [D_N^A(s)]$. Therefore

$$\begin{aligned} &\mathbf{E}_u^{\tau_N} [D_N^A(t)] + \mathbf{E}_u^{\tau_N} [D_N^A(s)] - \mathbf{E}_u^{\tau_N} [D_N^A(t + s)] \\ &= \mathbf{E}_u^{\tau_N} [D_N^A(t) + D_N^A(t \rightarrow s) - D_N^A(t + s)]. \end{aligned}$$

This last quantity is bounded by the number of sites that are discovered both before time t and also between times t and $t + s$ i.e. $|\mathcal{D}_N^A(t) \cap \mathcal{D}_N^A(t \rightarrow s)|$.

The Markov property (applied at time t) and the reversibility of u_N imply that $|\mathcal{D}_N^A(t) \cap \mathcal{D}_N^A(t \rightarrow s)|$ has the same law as $D_N^A(s, t)$, thus leading to the inequality in Lemma 5.6. □

We deduce from Lemma 5.6 that, for all $t > 0$,

$$\frac{\overline{\mathbb{E}}_N [D_N(t\mathbf{t}_N)]}{t \overline{\mathbb{E}}_N [D_N(\mathbf{t}_N)]} \xrightarrow{N \rightarrow +\infty} 1. \tag{5.11}$$

The upper bound in (5.11) follows from the integrated version of the first inequality in Lemma 5.6. To get the lower bound, we also take the expectation in the second inequality in Lemma 5.6 and iterate it approximately t times. The cumulated error term is estimated with Lemma 5.5: neglecting subexponential terms, it is of order $2^{-N} \mathbf{t}_N^2$. On the other hand, we already know from (5.6) that $\overline{\mathbb{E}}_N [D_N(\mathbf{t}_N)]$ is of the same order as \mathbf{t}_N on the exponential scale. Since $2^{-N} \mathbf{t}_N^2$ is negligible compared to \mathbf{t}_N , we can conclude the proof.

Our next task is to get estimates on the variance of $D_N^A(t)$. We shall use the notation $\mathbf{V}_u^{\tau_N}(X)$ to denote the variance of a random variable X under $\mathbf{P}_u^{\tau_N}$ and $\mathbf{C}_u^{\tau_N}(X, Y)$ to denote the covariance of the random variables X and Y under $\mathbf{P}_u^{\tau_N}$.

We obviously have

$$\mathbf{V}_u^{\tau_N}(X + Y) \leq \mathbf{V}_u^{\tau_N}(X) + \mathbf{E}_u^{\tau_N}(Y^2) + 2\mathbf{C}_u^{\tau_N}(X, Y). \tag{5.12}$$

If we write that $D_N^A(t+s) = D_N^A(t) + (D_N^A(t+s) - D_N^A(t))$, we are lead to estimating $\mathbf{C}_u^{\tau_N} [D_N^A(t), D_N^A(t+s) - D_N^A(t)]$.

Observe that $D_N^A(t+s) - D_N^A(t) \leq D_N^A(t \rightarrow s)$ (where $D_N^A(t \rightarrow s)$ was defined in (5.10)), and therefore

$$\mathbf{E}_u^{\tau_N} [D_N^A(t)(D_N^A(t+s) - D_N^A(t))] \leq \mathbf{E}_u^{\tau_N} [D_N^A(t)D_N^A(t \rightarrow s)].$$

On the other hand we read from Lemma 5.6 that $\mathbf{E}_u^{\tau_N} [D_N^A(t+s) - D_N^A(t)] \geq \mathbf{E}_u^{\tau_N} [D_N^A(s)] - \mathbf{E}_u^{\tau_N} [D_N^A(s, t)]$.

Thus we have

$$\begin{aligned} & \mathbf{C}_u^{\tau_N} [D_N^A(t), D_N^A(t+s) - D_N^A(t)] \\ & \leq \mathbf{C}_u^{\tau_N} [D_N^A(t), D_N^A(t \rightarrow s)] + \mathbf{E}_u^{\tau_N} [D_N^A(t)] \mathbf{E}_u^{\tau_N} [D_N^A(s, t)]. \end{aligned} \tag{5.13}$$

Lemma 5.7 *For all t and $s \geq N^2$ we have*

$$\mathbf{C}_u^{\tau_N} [D_N^A(t), D_N^A(t \rightarrow s)] \leq 2c(2)|A|^2(1 + \overline{\omega}_N t)(1 + \overline{\omega}_N N^2) + 2^{3N} e^{-2N^2}.$$

Proof We start observing that

$$\begin{aligned} & \mathbf{C}_u^{\tau_N} [D_N^A(t), D_N^A(t + N^2 \rightarrow s - N^2)] \\ & \leq 2^N e^{-2N^2} \mathbf{E}_u^{\tau_N} [D_N^A(t)] \mathbf{E}_u^{\tau_N} [D_N^A(t \rightarrow s)] \leq 2^{3N} e^{-2N^2}. \end{aligned}$$

(The first inequality is a consequence of Proposition 3.4, and the second one is obvious.)

Therefore

$$\begin{aligned} & \mathbf{C}_u^{\tau_N} \left[D_N^A(t), D_N^A(t \rightarrow s) \right] \\ & \leq \mathbf{C}_u^{\tau_N} \left[D_N^A(t), D_N^A(t + N^2 \rightarrow s - N^2) \right] + \mathbf{E}_u^{\tau_N} \left[D_N^A(t) D_N^A(t \rightarrow N^2) \right] \\ & \quad + \mathbf{E}_u^{\tau_N} \left[D_N^A(t) \right] \left(\mathbf{E}_u^{\tau_N} \left[D_N^A(t + N^2 \rightarrow s - N^2) \right] - \mathbf{E}_u^{\tau_N} \left[D_N^A(t \rightarrow s) \right] \right) \\ & \leq 2^{3N} e^{-2N^2} + \mathbf{E}_u^{\tau_N} \left[D_N^A(t) D_N^A(t \rightarrow N^2) \right] + \mathbf{E}_u^{\tau_N} \left[D_N^A(t) \right] \mathbf{E}_u^{\tau_N} \left[D_N^A(t \rightarrow N^2) \right] \\ & \leq 2^{3N} e^{-2N^2} + 2 \mathbf{E}_u^{\tau_N} \left[D_N^A(t)^2 \right]^{1/2} \mathbf{E}_u^{\tau_N} \left[D_N^A(N^2)^2 \right]^{1/2}. \end{aligned}$$

One now concludes the proof using the estimates from Lemma 5.4. □

Lemma 5.8

$$\frac{D_N^A(\mathbf{t}_N)}{\mathbf{E}_u^{\tau_N} \left[D_N^A(\mathbf{t}_N) \right]} \xrightarrow[N \rightarrow +\infty]{\mathbb{P}_N\text{-prob.}} 1.$$

Proof We split the time interval $[0, \mathbf{t}_N]$ into K pieces of equal size. Here K has to be chosen properly: $K = e^{N^{3/4}}$ would do.

We then estimate the variance of $D_N^A(\mathbf{t}_N)$ using (5.12) and (5.13):

$$\begin{aligned} \mathbf{V}_u^{\tau_N} \left[D_N^A(\mathbf{t}_N) \right] & \leq \mathbf{V}_u^{\tau_N} \left[D_N^A \left(\frac{K-1}{K} \mathbf{t}_N \right) \right] + \mathbf{E}_u^{\tau_N} \left[D_N^A \left(\frac{1}{K} \mathbf{t}_N \right)^2 \right] \\ & \quad + 2 \mathbf{C}_u^{\tau_N} \left[D_N^A \left(\frac{K-1}{K} \mathbf{t}_N \right), D_N^A \left(\frac{K-1}{K} \mathbf{t}_N \rightarrow \frac{1}{K} \mathbf{t}_N \right) \right] \\ & \quad + \mathbf{E}_u^{\tau_N} \left[D_N^A(\mathbf{t}_N) \right] \mathbf{E}_u^{\tau_N} \left[D_N^A \left(\frac{1}{K} \mathbf{t}_N, \frac{K-1}{K} \mathbf{t}_N \right) \right]. \end{aligned}$$

Using our estimates from Lemmas 5.4, 5.7, 5.3 and 5.5, we get that

$$\mathbf{V}_u^{\tau_N} \left[D_N^A(\mathbf{t}_N) \right] \leq \mathbf{V}_u^{\tau_N} \left[D_N^A \left(\frac{K-1}{K} \mathbf{t}_N \right) \right] + \eta_N,$$

where

$$\begin{aligned} \eta_N & = c(2)|A|^2 \left(1 + (\bar{\omega}_N \frac{1}{K} \mathbf{t}_N)^2 \right) + 4c(2)|A|^2 \left(1 + \bar{\omega}_N \mathbf{t}_N \right) \left(1 + \bar{\omega}_N N^2 \right) + 2^{3N} e^{-2N^2} \\ & \quad + 3\mathbf{t}_N |A| \left(1 + \bar{\omega}_N \right) 9 \left(1 + 2^{-N} \mathbf{t}_N^2 \right) |A|^2 \left(1 + \bar{\omega}_N \right). \end{aligned}$$

We iterate this computation K times. This way we get that $\mathbf{V}_u^{\tau_N} \left[D_N^A(\mathbf{t}_N) \right] \leq K \eta_N$.

It then follows from our assumptions on K that η_N is negligible compared with \mathbf{t}_N^2/K . (Observe in particular that, by Lemma 5.2, we have $(\bar{\omega}_N \frac{1}{K} \mathbf{t}_N)^2 \ll \mathbf{t}_N^2/K$.)

Thus we deduce that $K \eta_N / \mathbf{t}_N^2$ tends to 0 in \mathbb{P}_N -probability.

We have checked that the variance of $D_N^A(t_N)$ is negligible compared with the square of its mean with high $\bar{\mathbb{P}}_N$ -probability, and this ends the proof. (Recall that t_N is a lower bound for the mean of $D_N^A(t_N)$, see Lemma 5.3.) \square

End of the proof of Theorem 5.1 In order to deduce Theorem 5.1 from Lemma 5.8, it is sufficient to show that the variance of $\mathbf{E}_u^{\tau_N} [D_N(t_N)]$ under \mathbb{P} (i.e. as a function of the random variable τ_N) is negligible compared to t_N^2 .

We use the notation $\mathbb{V}[\mathbf{X}]$ to denote the variance of a random variable \mathbf{X} with respect to \mathbb{P} .

To estimate $\mathbb{V}[\mathbf{E}_u^{\tau_N} [D_N(t_N)]]$, we first rely on the Efron–Stein inequality (see [40]), namely

$$\mathbb{V}[\mathbf{E}_u^{\tau_N} [D_N(t_N)]] \leq \frac{1}{2} \sum_{x \in V_N} \mathbb{E} \left[\left(\mathbf{E}_u^{\tau_N} [D_N(t_N)] - \mathbf{E}_u^{\tau_N^{(x)}} [D_N(t_N)] \right)^2 \right],$$

where $\tau_N^{(x)}$ denotes an environment of traps in which we have replaced E_x by an independent copy and left all other values unchanged.

By symmetry, all the terms in this last sum have the same value, so that

$$\mathbb{V}[\mathbf{E}_u^{\tau_N} [D_N(t_N)]] \leq 2^{N-1} \mathbb{E} \left[\left(\mathbf{E}_u^{\tau_N} [D_N(t_N)] - \mathbf{E}_u^{\tau_N^{(0)}} [D_N(t_N)] \right)^2 \right].$$

Thus we see that we will be done if we prove that

$$2^N \mathbb{E} \left[\left(\mathbf{E}_u^{\tau_N} [D_N(t_N)] - \mathbf{E}_u^{\tau_N^{(0)}} [D_N(t_N)] \right)^2 \right]$$

is negligible with respect to t_N^2 . We will in fact show that, on the exponential scale, $\mathbb{E}[(\mathbf{E}_u^{\tau_N} [D_N(t_N)] - \mathbf{E}_u^{\tau_N^{(0)}} [D_N(t_N)])^2]$ is at most of order $(2^{-N} t_N)^2$:

$$\limsup_N \frac{1}{N} \log \mathbb{E}[(\mathbf{E}_u^{\tau_N} [D_N(t_N)] - \mathbf{E}_u^{\tau_N^{(0)}} [D_N(t_N)])^2] \leq 2 \lim_N \frac{1}{N} \log(2^{-N} t_N). \tag{5.14}$$

In order to show (5.14), we split the trajectory of the walk in different time intervals: let T_1 be the first time the point 0 is discovered by the process X ; let $\mathsf{T}^{(1)}$ be the first strong stationary time after T_1 : in other words, $\mathsf{T}^{(1)} - T_1$ is a strong stationary time for the Markov chain $(X_{t+T_1})_{t \geq 0}$ obtained as in Proposition 3.1.

We iterate these definitions: let T_2 be the first time 0 is discovered after time $\mathsf{T}^{(1)}$; let $\mathsf{T}^{(2)}$ be the first strong stationary time after time T_2 , ... We define $I_j = [T_j, \mathsf{T}^{(j)})$ and $I = \cup_j I_j$.

Let us also define

$$\mathcal{D}_N^{(0)}(t) = \{x \in V_N : \exists s \leq t, s \notin I \text{ s.t. } |X_s - x| \leq 1\},$$

and $D_N^{(0)}(t) = |\mathcal{D}_N^{(0)}(t)|$.

From the construction of strong stationary times, see Proposition 3.1 and its proof, it follows that the law of $\mathcal{D}_N^{(0)}(t)$ (and therefore the law of $D_N^{(0)}(t)$ and its mean) is the same under $\mathbf{P}_u^{\tau_N}$ or $\mathbf{P}_u^{\tau_N^{(0)}}$. Therefore $\mathbf{E}_u^{\tau_N}[D_N^{(0)}(t_N)] = \mathbf{E}_u^{\tau_N^{(0)}}[D_N^{(0)}(t_N)]$ and

$$\begin{aligned} & \mathbf{E}_u^{\tau_N}[D_N(t_N)] - \mathbf{E}_u^{\tau_N^{(0)}}[D_N(t_N)] \\ &= \mathbf{E}_u^{\tau_N}[D_N(t_N) - D_N^{(0)}(t_N)] - \mathbf{E}_u^{\tau_N^{(0)}}[D_N(t_N) - D_N^{(0)}(t_N)]. \end{aligned}$$

Note that these two terms have the same law under \mathbb{P} . Thus we will have established (5.14) once we show that $\mathbb{E}[\mathbf{E}_u^{\tau_N}[D_N(t_N) - D_N^{(0)}(t_N)]^2]$ is at most of order $(2^{-N}t_N)^2$ (up to subexponential factors).

Applying the Markov property and using the stationarity of the uniform probability, we have

$$\left| \mathbf{E}_u^{\tau_N}[D_N(t_N) - D_N^{(0)}(t_N)] \right| \leq \max_{x \sim 0} \mathbf{E}_x^{\tau_N}[D_N(\mathsf{T}_N)] \sum_{k \geq 1} \mathbf{P}_u^{\tau_N}[T_k \leq t_N],$$

where T_N is the strong stationary time considered in Proposition 3.1. It is easy to deduce from Proposition 3.1 and Lemma 5.4 that $\max_{x \sim 0} \mathbf{E}_x^{\tau_N}[D_N(\mathsf{T}_N)]$ is of subexponential order.

To bound the second term, observe that, when the process X hits a point x , it then spends at x an exponentially distributed time of parameter $\omega_N(x) \leq \bar{\omega}_N$. Therefore, for all $\lambda > 0$,

$$\mathbf{E}_u^{\tau_N} \left[\int_0^{+\infty} e^{-\lambda s} \mathbf{1}_{X_s \sim 0} ds \right] \geq \frac{1}{\lambda + \bar{\omega}_N} \mathbf{E}_u^{\tau_N} \left[e^{-\lambda T_1} \right].$$

But, due to the stationarity of the uniform probability, we also have

$$\mathbf{E}_u^{\tau_N} \left[\int_0^{+\infty} e^{-\lambda s} \mathbf{1}_{X_s \sim 0} ds \right] = \frac{N + 1}{2^N} \frac{1}{\lambda}.$$

Therefore

$$\mathbf{E}_u^{\tau_N} \left[e^{-\lambda T_1} \right] \leq \frac{N + 1}{2^N} \frac{\lambda + \bar{\omega}_N}{\lambda}.$$

Choosing $\lambda = 1/t$ yields

$$\mathbf{E}_u^{\tau_N} \left[e^{-T_1/t} \right] \leq \frac{N + 1}{2^N} (1 + \bar{\omega}_N t).$$

Observe that T_k stochastically dominates a sum of k independent copies of T_1 . Therefore

$$\mathbf{E}_u^{\tau_N} \left[e^{-T_k/t} \right] \leq \left(\frac{N+1}{2^N} (1 + \bar{\omega}_N t) \right)^k,$$

which leads to

$$\sum_{k \geq 1} \mathbf{P}_u^{\tau_N} [T_k \leq t] \leq 2e \frac{N+1}{2^N} (1 + \bar{\omega}_N t), \tag{5.15}$$

whenever $\frac{N+1}{2^N} (1 + \bar{\omega}_N t) \leq \frac{1}{2}$.

On the other hand, $\mathbf{E}_u^{\tau_N} [D_N(t_N) - D_N^{(0)}(t_N)] \leq 2^N$. Thus we have

$$\begin{aligned} & \mathbf{E}_u^{\tau_N} \left[D_N(t_N) - D_N^{(0)}(t_N) \right] \\ & \leq \left(2^N \mathbf{1} \left(\frac{N+1}{2^N} (1 + \bar{\omega}_N t_N) \geq \frac{1}{2} \right) + \max_{x \sim 0} \mathbf{E}_x^{\tau_N} [D_N(\mathbb{T}_N)] 2e \frac{N+1}{2^N} (1 + \bar{\omega}_N t_N) \right). \end{aligned}$$

We now have to square this last inequality and take the expectation with respect to \mathbb{P} . The \mathbb{P} probability of the event $\frac{N+1}{2^N} (1 + \bar{\omega}_N t_N) \geq \frac{1}{2}$ decays to 0 at a super-exponential rate (see (5.3)), which compensates for the 2^N factor in front. We already noticed that $\max_{x \sim 0} \mathbf{E}_x^{\tau_N} [D_N(\mathbb{T}_N)]$ is of subexponential order and the term $(1 + \bar{\omega}_N t_N)$ is of the same order as t_N (still on the exponential scale). Thus we conclude that $\mathbb{E}[\mathbf{E}_u^{\tau_N} [D_N(t_N) - D_N^{(0)}(t_N)]^2]$ is at most of order $(2^{-N} t_N)^2$ and therefore (5.14) holds. \square

6 Defining the scales

We fix $\bar{c} \in (0, \log(2))$, and t_N such that $\log(t_N) \sim \bar{c}N$. The sequence t_N is our time scale for the accelerated dynamics X . Theorem 5.1 associates with it a second scale (d_N) measuring the number of sites discovered, and we recall that $\log(d_N) \sim \bar{c}N$.

It is a classical fact that

$$\mathbb{P}[E_x \geq z] \sim \frac{1}{z\sqrt{2\pi}} e^{-z^2/2} \quad (z \rightarrow +\infty). \tag{6.1}$$

Letting

$$b_N = (2 \log d_N)^{1/2} - \frac{1}{2(2 \log d_N)^{1/2}} (\log \log d_N + \log(4\pi)),$$

we obtain

$$\mathbb{P}[E_x \geq b_N] \sim d_N^{-1}. \tag{6.2}$$

Since by Proposition 4.1, the random variables $(E_{x_i})_{1 \leq i \leq d_N}$ are i.i.d. under $\bar{\mathbb{P}}_N$, their maxima will be of the order of b_N . In order to measure the maximal values of $(\tau_{N,x_i})_{1 \leq i \leq d_N}$, we thus define

$$B_N = e^{\beta\sqrt{N}b_N}. \tag{6.3}$$

Using the fact that $\log(\mathbf{d}_N) \sim \bar{c}N$, one can show that for any $z > 0$,

$$\mathbb{P} [\tau_{N,x} \geq zB_N] \sim \mathbf{d}_N^{-1} z^{-\alpha}, \tag{6.4}$$

where

$$\alpha = \frac{\sqrt{2\bar{c}}}{\beta}. \tag{6.5}$$

As a way to make it clear that the scale chosen is the correct one, we note for instance that

$$\bar{\mathbb{P}}_N \left[\max_{1 \leq i \leq \mathbf{d}_N} \tau_{N,x_i} \leq zB_N \right] \xrightarrow{N \rightarrow \infty} \exp(-z^{-\alpha}).$$

From now on, we assume that $\alpha < 1$, which corresponds to a low temperature assumption, and is the regime of aging. Actually, this assumption is only required at the very end of our proof, in order to show that the time spent out of deep traps is negligible. Specifically, we will need the following result.

Proposition 6.1 *We assume $\alpha < 1$. We have*

$$\limsup_{N \rightarrow +\infty} \frac{\mathbf{d}_N}{B_N} \mathbb{E} [\tau_{N,x} \mathbf{1}_{\tau_{N,x} \leq \delta B_N}] = O(\delta^{1-\alpha}) \quad (\delta \rightarrow 0). \tag{6.6}$$

Proof This can be justified using the general results of [5], but we prefer to provide the reader with a more direct proof. We can write $\mathbb{E} [\tau_{N,x} \mathbf{1}_{\tau_{N,x} \leq \delta B_N}]$ as

$$1/2 + \frac{1}{\sqrt{2\pi}} \int_0^{+\infty} e^{\beta\sqrt{N}u} e^{-u^2/2} \mathbf{1}_{e^{\beta\sqrt{N}u} \leq \delta B_N} du. \tag{6.7}$$

The condition on the indicator function can be rewritten as

$$u \leq b_N + \frac{\log(\delta)}{\beta\sqrt{N}}.$$

We let

$$u_N = \frac{b_N}{\sqrt{N}} + \frac{\log(\delta)}{\beta N}.$$

Note that u_N tends to $\sqrt{2\bar{c}}$ as N tends to infinity. In (6.7), the term $1/2$ can be neglected since the integral is bounded away from 0 (or because one can easily check that B_N/\mathbf{d}_N grows exponentially fast with N). By a change of variables, we can rewrite this integral as

$$\sqrt{N} \int_0^{u_N} e^{N(\beta u - u^2/2)} du. \tag{6.8}$$

We write $f(u) = \beta u - u^2/2$. Since f is concave, we have

$$f(u) \leq f(u_N) + (u - u_N)f'(u_N),$$

and thus the quantity appearing in (6.8) is bounded by

$$\sqrt{N} e^{Nf(u_N)} \int_0^{u_N} e^{N(u-u_N)f'(u_N)} du \leq \frac{1}{f'(u_N)\sqrt{N}} e^{Nf(u_N)}. \tag{6.9}$$

The term $f'(u_N)$ converges to $f'(\sqrt{2c}) > 0$. We need to compute $f(u_N)$:

$$Nf(u_N) = \beta\sqrt{N}b_N + \log(\delta) - \frac{b_N^2}{2} - \frac{b_N}{\beta\sqrt{N}} \log(\delta) - \underbrace{\frac{\log^2(\delta)}{\beta N}}_{\rightarrow 0}.$$

Recalling that $B_N = e^{\beta\sqrt{N}b_N}$, we obtain the right-hand side of (6.9) is bounded, up to a constant, by

$$\frac{B_N e^{-b_N^2/2}}{\sqrt{N}} \exp\left(\underbrace{\left[1 - \frac{b_N}{\beta\sqrt{N}}\right]}_{\rightarrow 1-\alpha} \log(\delta)\right).$$

The result is thus proved provided

$$\frac{e^{-b_N^2/2}}{\sqrt{N}} = O(d_N^{-1}),$$

but this is a consequence of (6.1) and (6.2). □

Remark 6.2 A slightly more careful analysis reveals that actually,

$$\lim_{N \rightarrow +\infty} \frac{d_N}{B_N} \mathbb{E}[\tau_{N,x} \mathbf{1}_{\tau_{N,x} \leq \delta B_N}] = \frac{\alpha}{1-\alpha} \delta^{1-\alpha}.$$

7 The deep traps

Let $\delta > 0$. We say that $x \in V_N$ is a *deep trap* if $\tau_{N,x} \geq \delta B_N$. Let $(r_N^{(\delta)}(n))_{n \in \mathbb{N}}$ be the increasing sequence spanning the set

$$\{i \in \mathbb{N} : \tau_{N,x_i} \geq \delta B_N\},$$

with the convention that $r_N^{(\delta)}(n) = +\infty$ if n exceeds the cardinality of this set. In other words, in the numbering defined by the exploration process, $r_N^{(\delta)}(1)$ is the index of the first deep trap discovered by the random walk, $r_N^{(\delta)}(2)$ is the index of the second one, and so on. When $r_N^{(\delta)}(n)$ is finite, we let $x_N^{(\delta)}(n)$ be the position of the n th trap discovered, that is, $x_N^{(\delta)}(n) = x_{r_N^{(\delta)}(n)}$. We set $x_N^{(\delta)}(n) = \infty$ if $r_N^{(\delta)}(n) = +\infty$. The quantity $\tau_{N,x_N^{(\delta)}(n)}$ denotes the depth of the n th trap discovered, with the understanding that $\tau_{N,x_N^{(\delta)}(n)} = \infty$ when $x_N^{(\delta)}(n) = \infty$. Let $T_N^{(\delta)}(n)$ be the instant when the n th trap is discovered:

$$T_N^{(\delta)}(n) = \inf \left\{ t : D_N(t) \geq r_N^{(\delta)}(n) \right\} = \inf \left\{ t : x_N^{(\delta)}(n) \in \mathcal{D}_N(t) \right\} \quad (+\infty \text{ if empty}).$$

Proposition 7.1 *Under $\bar{\mathbb{P}}_N$, the random variables*

$$\left((t_N^{-1} T_N^{(\delta)}(n), B_N^{-1} \tau_{N,x_N^{(\delta)}(n)}) \right)_{n \in \mathbb{N}}$$

jointly converge in distribution as N tends to infinity (in the sense of finite-dimensional distributions). Let us write

$$\left((T^{(\delta)}(n), \tau^{(\delta)}(n)) \right)_{n \in \mathbb{N}}$$

for limiting random variables, which we assume to be defined on the \mathbb{P} -probability space for convenience. Their joint distribution is described as follows. The family $(T^{(\delta)}(n))_{n \in \mathbb{N}}$ is distributed as the jump instants of a Poisson process of intensity $\delta^{-\alpha}$, while $(\tau^{(\delta)}(n))_{n \in \mathbb{N}}$ are i.i.d. with common distribution

$$\alpha \delta^\alpha \frac{dz}{z^{\alpha+1}} \mathbf{1}_{[\delta, +\infty)}(z). \tag{7.1}$$

Moreover, the two families $(T^{(\delta)}(n))_{n \in \mathbb{N}}$ and $(\tau^{(\delta)}(n))_{n \in \mathbb{N}}$ are independent.

Proof Recall that as given by Proposition 4.1, the random variables $(\tau_{N,x_j})_{1 \leq j \leq 2^N}$ are i.i.d. Let us write

$$p_N = \bar{\mathbb{P}}_N [x_j \text{ deep trap}] = \bar{\mathbb{P}}_N [\tau_{N,x_j} \geq \delta B_N].$$

Recall from (6.4) that

$$d_N p_N \xrightarrow{N \rightarrow \infty} \delta^{-\alpha}. \tag{7.2}$$

Let F_n be the σ -algebra generated by $(\tau_{N,x_j})_{1 \leq j \leq r_N^{(\delta)}(n)}$. For $k \in \mathbb{N}$ and $z \geq \delta$, we compute

$$\bar{\mathbb{P}}_N \left[r_N^{(\delta)}(n) = k + r_N^{(\delta)}(n-1), B_N^{-1} \tau_{N,x_N^{(\delta)}(n)} \geq z \mid F_{n-1} \right].$$

The event $r_N^{(\delta)}(n) = k + r_N^{(\delta)}(n - 1)$ corresponds to the fact that for every j such that $r_N^{(\delta)}(n - 1) < j < k + r_N^{(\delta)}(n - 1)$, the site x_j is not a deep trap, while $x_{k+r_N^{(\delta)}(n-1)}$ is a deep trap. This event is independent of F_{n-1} and has probability

$$p_N(1 - p_N)^{k-1}.$$

Conditionally on $r_N^{(\delta)}(n) = k + r_N^{(\delta)}(n - 1)$ and on F_{n-1} , the probability of the event

$$B_N^{-1} \tau_{N,x_N^{(\delta)}}(n) \geq z$$

is nothing but

$$\mathbb{P}[\tau_{N,0} \geq zB_N \mid \tau_{N,0} \geq \delta B_N].$$

Hence, we obtain

$$\begin{aligned} \bar{\mathbb{P}}_N \left[r_N^{(\delta)}(n) = k + r_N^{(\delta)}(n - 1), B_N^{-1} \tau_{N,x_N^{(\delta)}}(n) \geq z \mid F_{n-1} \right] \\ = p_N(1 - p_N)^{k-1} \mathbb{P}[\tau_{N,0} \geq zB_N \mid \tau_{N,0} \geq \delta B_N]. \end{aligned}$$

Summing over k leads to

$$\begin{aligned} \bar{\mathbb{P}}_N \left[r_N^{(\delta)}(n) > k + r_N^{(\delta)}(n - 1), B_N^{-1} \tau_{N,x_N^{(\delta)}}(n) \geq z \mid F_{n-1} \right] \\ = (1 - p_N)^k \mathbb{P}[\tau_{N,0} \geq zB_N \mid \tau_{N,0} \geq \delta B_N]. \end{aligned}$$

In view of (7.2) and of the fact that (see (6.4))

$$\mathbb{P}[\tau_{N,0} \geq zB_N \mid \tau_{N,0} \geq \delta B_N] \xrightarrow{N \rightarrow \infty} \frac{\delta^\alpha}{z^\alpha},$$

we obtain that under $\bar{\mathbb{P}}_N$, the random variables

$$\left((d_N^{-1} r_N^{(\delta)}(n), B_N^{-1} \tau_{N,x_N^{(\delta)}}(n)) \right)_{n \in \mathbb{N}} \tag{7.3}$$

jointly converge in distribution to the random variables

$$\left((T^{(\delta)}(n), \tau^{(\delta)}(n)) \right)_{n \in \mathbb{N}} \tag{7.4}$$

described in the proposition. To conclude, we need to replace the random variables $d_N^{-1} r_N^{(\delta)}(n)$ by $t_N^{-1} T_N^{(\delta)}(n)$ in the convergence of (7.3) to (7.4).

The process $t \mapsto D_N(t)$ is increasing, right-continuous, and the size of its jumps cannot be larger than $(N + 1)$ since the walk discovers at most $(N + 1)$ sites at once. Hence,

$$r_N^{(\delta)}(n) \leq D_N(T_N^{(\delta)}(n)) \leq r_N^{(\delta)}(n) + N + 1.$$

Since d_N grows exponentially in N , it follows that in the convergence of (7.3) to (7.4), we can replace $d_N^{-1} r_N^{(\delta)}(n)$ by $d_N^{-1} D_N(T_N^{(\delta)}(n))$.

Let us see that for any $y > 0$,

$$\mathbb{P}_N \left[\mathfrak{t}_N^{-1} T_N^{(\delta)}(1) \geq y \right] \xrightarrow{N \rightarrow \infty} e^{-y\delta^{-\alpha}}. \tag{7.5}$$

For any $\varepsilon > 0$, we have

$$\begin{aligned} & \mathbb{P}_N \left[T_N^{(\delta)}(1) \geq \mathfrak{t}_N(y + \varepsilon) \right] \\ & \leq \mathbb{P}_N \left[D_N(T_N^{(\delta)}(1)) \geq d_N y \right] + \mathbb{P}_N \left[D_N(\mathfrak{t}_N(y + \varepsilon)) < d_N y \right]. \end{aligned}$$

The first term tends to $e^{-y\delta^{-\alpha}}$ by the preceding observation, while the second tends to 0 by Theorem 5.1. Hence,

$$\limsup_{N \rightarrow +\infty} \mathbb{P}_N \left[T_N^{(\delta)}(1) \geq \mathfrak{t}_N(y + \varepsilon) \right] \leq e^{-y\delta^{-\alpha}}. \tag{7.6}$$

Similarly, one can show that

$$\liminf_{N \rightarrow +\infty} \mathbb{P}_N \left[T_N^{(\delta)}(1) \geq \mathfrak{t}_N(y - \varepsilon) \right] \geq e^{-y\delta^{-\alpha}}. \tag{7.7}$$

Inequalities (7.6) and (7.7) being valid for any $\varepsilon > 0$, they justify (7.5). The generalization of this identity to the convergence of finite-dimensional distributions is then only a matter of notation (the key point besides Theorem 5.1, as seen in the proof of (7.5), being the monotonicity of $t \mapsto D_N(t)$). \square

8 The environment viewed by the particle

Let $\Omega_N = [1, +\infty)^{V_N}$, so that τ_N is a random variable taking values in Ω_N . The group V_N naturally acts on Ω_N by translations: for $\tau \in \Omega_N$ and $x \in V_N$, we let $\theta_x \tau \in \Omega_N$ be such that

$$(\theta_x \tau)_z = \tau_{x+z}.$$

We define the *environment viewed by the particle* as the process $(\tau_N(t))_{t \geq 0}$, taking values in Ω_N and such that

$$\tau_N(t) = \theta_{X_t} \tau_N.$$

Proposition 8.1 *For any $\tau_N \in \Omega_N$, the process $(\tau_N(t))_{t \geq 0}$ is a reversible Markov chain under the measure $\mathbf{P}_u^{\tau_N}$.*

Proof The Markov property of this process is inherited from (X_t) . A minor adaptation of the proof of [21, Lemma 4.3 (iv)] shows reversibility. \square

9 The environment around the first trap discovered

Let us write $\tau_N^{(\delta)}(n)$ for the environment seen at $x_N^{(\delta)}(n)$, that is,

$$\tau_N^{(\delta)}(n) = \theta_{x_N^{(\delta)}(n)} \tau_N.$$

The main purpose of this section is to understand the distribution of $\tau_N^{(\delta)}(1)$. Let

$$G_N(\tau_N) = \mathbf{E}_0^{\tau_N} \left[\int_0^{+\infty} e^{-t/N^2} \mathbf{1}_{X_t=0} dt \right]. \tag{9.1}$$

The value of $\tau_N^{(\delta)}(1)$ at 0 is described by Proposition 7.1. Roughly speaking, we will show that as N tends to infinity, the distribution of $(\tau_N^{(\delta)}(1))_{z \neq 0}$ approaches the distribution proportional to

$$\frac{1}{G_N(\tau_N)} d\mathbb{P}(\tau_N).$$

More precisely, we will prove the following result.

Theorem 9.1 *Let $\mathcal{H}_N^{(\delta)}(n)$ be the event that $x_N^{(\delta)}(n)$ is visited by X during the time interval $[T_N^{(\delta)}(n), T_N^{(\delta)}(n) + N]$. For $M > 0$, let \mathcal{E}_N^M be the event defined by*

$$T_N^{(\delta)}(1) \leq M t_N \quad \text{and} \quad \mathcal{H}_N^{(\delta)}(1) \text{ holds.} \tag{9.2}$$

For any $\varepsilon > 0$, any M large enough and any N large enough, if $h_N : \Omega_N \rightarrow \mathbb{R}$ is such that $\|h_N\|_\infty \leq 1$, then

$$\bar{\mathbb{E}}_N \left[(h_N G_N)(\tau_N^{(\delta)}(1)), \mathcal{E}_N^M \right] = \frac{t_N}{d_N} \left(\mathbb{E} [h_N(\tau_N) \mid \tau_{N,0} \geq \delta B_N] \pm \varepsilon \right), \tag{9.3}$$

where we recall that the notation \pm was introduced at the end of Sect. 1.

Remark 9.2 In (9.3) and below, for any $\tau \in \Omega_N$, we write $(h_N G_N)(\tau)$ as shorthand for $h_N(\tau) G_N(\tau)$.

Remark 9.3 A notable feature of Theorem 9.1 is that as soon as N is large enough, identity (9.3) holds for any function h_N satisfying $\|h_N\|_\infty \leq 1$. In particular, it is not required that, for instance, h_N depend only on a finite number of $(\tau_{N,x})_{x \in V_N}$, or have any other form of spatial mixing property. This will make the proof of Theorem 9.1 slightly more involved than otherwise, but will also greatly simplify our subsequent reasoning.

We now describe our starting point for the proof of Theorem 9.1. Let us introduce $(\tilde{\epsilon}_N(n))_{n \in \mathbb{N}}$ i.i.d. exponential random variables of parameter $1/N^2$ (under $\mathbf{P}_x^{\tau_N}$ for any x), independent of everything else, and write $(\Theta_t)_{t \geq 0}$ to denote the time translations on the space of trajectories, that is, $(\Theta_t X)_s = X_{t+s}$. For any $M \geq 1$, we define $T_N^M(1) = T_N^{(\delta)}(1) \wedge (M\tau_N)$ (although this depends also on δ , we keep it implicit in the notation, since δ will be kept fixed as long as we consider this quantity). Letting $\tilde{T}_N^M(0) = 0$, we then define recursively, for any $n \in \mathbb{N}$,

$$T_N^M(n) = \tilde{T}_N^M(n-1) + T_N^M(1) \circ \Theta_{\tilde{T}_N^M(n-1)}, \tag{9.4}$$

$$\tilde{T}_N^M(n) = T_N^M(n) + \tilde{\epsilon}_N(n) + \mathbf{T}_N \circ \Theta_{T_N^M(n) + \tilde{\epsilon}_N(n)}. \tag{9.5}$$

In words, to reach time $\tilde{T}_N^M(n)$, we wait until the end of a strong stationary time (as given by Proposition 3.1) started at time $T_N^M(n) + \tilde{\epsilon}_N(n)$.

Proposition 9.4 *Under the measure $\mathbf{P}_u^{\tau_N}$, the successive pieces of trajectory*

$$\left((X_s)_{\tilde{T}_N^M(n-1) \leq s < \tilde{T}_N^M(n)} \right)_{n \in \mathbb{N}}$$

form a stationary sequence, while

$$\left((X_s)_{T_N^M(n-1) \leq s < T_N^M(n) + \tilde{\epsilon}_N(n)} \right)_{n \in \mathbb{N}}$$

are independent and identically distributed.

Proof The first part is a consequence of the Markov property and the fact that $X_{\tilde{T}_N^M(n)}$ is distributed uniformly over V_N , itself a consequence of the fact that \mathbf{T}_N is a stationary time.

For the second part, we only need to check the independence. Let F be a bounded function on the space of trajectories which is measurable with respect to the σ -algebra generated by $(X_s)_{s < T_N^M(n) + \tilde{\epsilon}_N(n)}$, and G be a bounded measurable function on the space of trajectories. We want to show that

$$\mathbf{E}_u^{\tau_N} \left[F \left(G \circ \Theta_{\tilde{T}_N^M(n+1)} \right) \right] = \mathbf{E}_u^{\tau_N} [F] \mathbf{E}_u^{\tau_N} [G]. \tag{9.6}$$

The left-hand side above is equal to

$$\mathbf{E}_u^{\tau_N} \left[F \mathbf{E}_{X_{T_N^M(n) + \tilde{\epsilon}_N(n)}}^{\tau_N} \left[G \circ \Theta_{\mathbf{T}_N} \right] \right],$$

and this leads to (9.6) by the Markov property and the fact that \mathbf{T}_N is a stationary time. □

Let $h_N : \Omega_N \rightarrow \mathbb{R}$ be a function. By the ergodic theorem, for any environment $\tau_N \in \Omega_N$,

$$t^{-1} \mathbf{E}_u^{\tau_N} \left[\int_0^{t\mathbf{t}_N} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} ds \right] \xrightarrow{t \rightarrow \infty} \frac{\mathbf{t}_N}{\mathbf{E}_u^{\tau_N} [\tilde{T}_N^M(1)]} \mathbf{E}_u^{\tau_N} \left[\int_0^{\tilde{T}_N^M(1)} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} ds \right]. \tag{9.7}$$

On the other hand, the stationarity of the environment viewed by the particle (that is, Proposition 8.1) guarantees that

$$\mathbf{E}_u^{\tau_N} \left[\int_0^{t\mathbf{t}_N} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} ds \right] = t\mathbf{t}_N \mathbf{E}_u^{\tau_N} \left[h_N(\tau_N(0)) \mathbf{1}_{\tau_N, X_0 \geq \delta B_N} \right].$$

Combining this with (9.7), we thus obtain that, for any environment,

$$\frac{1}{\mathbf{E}_u^{\tau_N} [\tilde{T}_N^M(1)]} \mathbf{E}_u^{\tau_N} \left[\int_0^{\tilde{T}_N^M(1)} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} ds \right] = \mathbf{E}_u^{\tau_N} \left[h_N(\tau_N(0)) \mathbf{1}_{\tau_N, X_0 \geq \delta B_N} \right],$$

which we can rewrite as

$$\mathbf{E}_u^{\tau_N} \left[\int_0^{\tilde{T}_N^M(1)} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} ds \right] = \mathbf{E}_u^{\tau_N} [\tilde{T}_N^M(1)] \mathbf{P}_u^{\tau_N} [\tau_N, X_0 \geq \delta B_N] \mathbf{E}_u^{\tau_N} [h_N(\tau_N(0)) | \tau_N, X_0 \geq \delta B_N], \tag{9.8}$$

where the conditional expectation is understood to be 1 in case the event $\tau_N, X_0 \geq \delta B_N$ has $\mathbf{P}_u^{\tau_N}$ -probability equal to 0 (that is, when τ_N contains no deep trap). The rest of this section is devoted to passing from (9.8) to Theorem 9.1. We want to take \mathbb{E} -expectations on both sides of this identity. Considering first the right-hand side, we prove that $\mathbf{P}_u^{\tau_N} [\tau_N, X_0 \geq \delta B_N]$ and $\mathbf{E}_u^{\tau_N} [\tilde{T}_N^M(1)]$ are concentrated respectively around $\delta^{-\alpha} \mathbf{d}_N^{-1}$ and $\delta^\alpha \mathbf{t}_N$.

Lemma 9.5 *There exists $c > 0$ such that for any $\varepsilon > 0$ and any N large enough,*

$$\mathbb{P} \left[\mathbf{P}_u^{\tau_N} [\tau_N, X_0 \geq \delta B_N] = (1 \pm \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1} \right] \geq 1 - \exp(-e^{cN}).$$

Proof We can rewrite the probability $\mathbf{P}_u^{\tau_N} [\tau_{N, X_0} \geq \delta B_N]$ as

$$|V_N|^{-1} \sum_{x \in V_N} \mathfrak{B}_{N,x},$$

where $\mathfrak{B}_{N,x} = \mathbf{1}_{\tau_{N,x} \geq \delta B_N}$. Under \mathbb{P} , the $(\mathfrak{B}_{N,x})_{x \in V_N}$ are independent Bernoulli random variables with parameter $p_N = \mathbb{P}[\mathfrak{B}_{N,x} = 1] \sim \delta^{-\alpha} \mathbf{d}_N^{-1}$ by (6.4). Lemma 9.5 thus reflects a classical large deviation estimate. More precisely, for any $\lambda > 0$,

$$\mathbb{P} \left[|V_N|^{-1} \sum_{x \in V_N} \mathfrak{B}_{N,x} > (1 + \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1} \right] \leq \frac{\mathbb{E}[e^{\lambda \mathfrak{B}_{N,0}}]^{|V_N|}}{\exp(\lambda |V_N| (1 + \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1})},$$

with

$$\mathbb{E}[e^{\lambda \mathfrak{B}_{N,0}}]^{|V_N|} = (1 - p_N + p_N e^\lambda)^{|V_N|} = \exp(|V_N| \log(1 + p_N(e^\lambda - 1))).$$

Recalling that $p_N \sim \delta^{-\alpha} \mathbf{d}_N^{-1}$, we see that if $\lambda > 0$ is chosen small enough and N is large, then

$$\log(1 + p_N(e^\lambda - 1)) \leq (1 + \varepsilon/2) \delta^{-\alpha} \mathbf{d}_N^{-1},$$

and since $|V_N| \mathbf{d}_N^{-1} \geq e^{cN}$ for some $c > 0$, we obtain, for any N large enough,

$$\mathbb{P} \left[|V_N|^{-1} \sum_{x \in V_N} \mathfrak{B}_{N,x} > (1 + \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1} \right] \leq \exp(-e^{cN}).$$

The probability

$$\mathbb{P} \left[|V_N|^{-1} \sum_{x \in V_N} \mathfrak{B}_{N,x} < (1 - \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1} \right]$$

is handled in the same way. □

Lemma 9.6 *For any $\varepsilon > 0$, any M large enough and any N large enough,*

$$\mathbf{P} \left[\mathbf{E}_u^{\tau_N} \left[\tilde{T}_N^M(1) \right] = (1 \pm \varepsilon) \delta^\alpha \mathbf{t}_N \right] \geq 1 - \varepsilon.$$

Proof The difference $\tilde{T}_N^M(1) - T_N^M(1)$ consists in the sum of the random variables $\tilde{e}_N(1)$, which is exponential with mean N^2 , and \mathbf{T}_N , which is of order N by Proposition 3.1. Since \mathbf{t}_N grows exponentially with N , it suffices to prove that the lemma holds with $T_N^M(1)$ instead of $\tilde{T}_N^M(1)$.

We know from Proposition 7.1 that $t_N^{-1} T_N^{(\delta)}(1)$ converges in law under $\bar{\mathbb{P}}_N$ to $T^{(\delta)}(1)$, an exponential random variable of parameter $\delta^{-\alpha}$. Recall that $T_N^M(1)$ is defined as $T_N^{(\delta)}(1) \wedge (Mt_N)$, and hence $t_N^{-1} T_N^M(1)$ converges in law to

$$T^{(\delta)}(1) \wedge M, \tag{9.9}$$

and is always bounded by M . As a consequence, for M and N large enough, we have

$$\mathbb{E} \mathbf{E}_u^{\tau_N} \left[T_N^M(1) \right] = (1 \pm \varepsilon/2) \delta^\alpha t_N.$$

In order to conclude, it thus suffices to show that the variance of $\mathbf{E}_u^{\tau_N} [T_N^M(1)]$ is much smaller than t_N^2 . The proof of this fact is similar to the end of the proof of Theorem 5.1, where we showed that the variance of $\mathbf{E}_u^{\tau_N} [D_N(t_N)]$ is much smaller than t_N^2 .

Recall that we write $\mathbb{V}[X]$ to denote the variance of the random variable X with respect to \mathbb{P} . By the Efron–Stein inequality and translation invariance, we have

$$\mathbb{V} \left[\mathbf{E}_u^{\tau_N} [T_N^M(1)] \right] \leq 2^{N-1} \mathbb{E} \left[\left(\mathbf{E}_u^{\tau_N} [T_N^M(1)] - \mathbf{E}_u^{\tau_N^{(0)}} [T_N^M(1)] \right)^2 \right],$$

where $\tau_N^{(0)}$ is the environment which coincides with τ_N , except at 0 where E_0 has been replaced by an independent copy of it. As in the proof of Theorem 5.1, we introduce T_1 the first time the point 0 is discovered by the process X ; we let $\mathbb{T}^{(1)}$ be the first strong stationary time after T_1 . We iterate these definitions: T_2 is the first time 0 is discovered after $\mathbb{T}^{(1)}$, then $\mathbb{T}^{(2)}$ is the first strong stationary time after T_2 , and so on. We define $I = \cup [T_j, \mathbb{T}^{(j)})$, and

$$T_N^{(0)} = \inf \{ t \geq 0, t \notin I : \exists x \text{ deep trap s.t. } |X_t - x| \leq 1 \} \wedge (Mt_N).$$

This definition would coincide with that of $T_N^M(1)$ if the constraint $t \notin I$ was suppressed. The quantity $T_N^{(0)}$ is convenient for our purpose, because its law under $\mathbf{P}_u^{\tau_N}$ does not depend on $\tau_{N,0}$, and is thus the same under $\mathbf{P}_u^{\tau_N}$ and under $\mathbf{P}_u^{\tau_N^{(0)}}$. We can thus write

$$\mathbf{E}_u^{\tau_N} [T_N^M(1)] - \mathbf{E}_u^{\tau_N^{(0)}} [T_N^M(1)] = \mathbf{E}_u^{\tau_N} [T_N^M(1) - T_N^{(0)}] - \mathbf{E}_u^{\tau_N^{(0)}} [T_N^M(1) - T_N^{(0)}].$$

Since these two terms have the same law under \mathbb{P} , it suffices for our purpose to show that

$$2^N \mathbb{E} \left[\left(\mathbf{E}_u^{\tau_N} [T_N^M(1) - T_N^{(0)}] \right)^2 \right] = o(t_N^2). \tag{9.10}$$

Let \mathcal{T} be the event defined by

$$\exists s \leq T_N, \ x \text{ deep trap s.t. } |X_s - x| \leq 1,$$

where T_N is the strong stationary time of Proposition 3.1. By the Markov property, we have

$$\mathbf{E}_u^{\tau_N} [T_N^M(1) - T_N^{(0)}] \leq M t_N \max_{x \sim 0} \mathbf{P}_x^{\tau_N} [T] \sum_{k \geq 1} \mathbf{P}_u^{\tau_N} [T_k \leq M t_N].$$

We have seen in (5.15) that the sum on the right-hand side gives a contribution which, up to sub-exponential factors, is bounded by $t_N/2^N$. There remains to evaluate

$$\mathbb{E} \left[\left(\max_{x \sim 0} \mathbf{P}_x^{\tau_N} [T] \right)^2 \right] \leq \mathbb{E} \left[\left(\sum_{x \sim 0} \mathbf{P}_x^{\tau_N} [T] \right)^2 \right] \leq N \sum_{x \sim 0} \mathbb{E} \left[\mathbf{P}_x^{\tau_N} [T]^2 \right] \leq N^2 \bar{\mathbb{P}}_N [T],$$

where in the last step, we simply bounded the square of the probability by the probability itself, and then used translation invariance. We will show that, up to sub-exponential factors, the quantity above is bounded by t_N^{-1} , that is,

$$\limsup_{N \rightarrow \infty} \frac{1}{N} \log \left(\bar{\mathbb{P}}_N [T] \right) \leq \lim_{N \rightarrow \infty} \frac{1}{N} \log(t_N^{-1}) \quad (= -\bar{c}). \tag{9.11}$$

Assuming this to be true, we obtain that up to sub-exponential factors, the left-hand side of (9.10) is bounded by

$$2^N \frac{t_N^2}{t_N} \left(\frac{t_N}{2^N} \right)^2 = t_N^2 \frac{t_N}{2^N}.$$

Since $\log(t_N) \sim \bar{c}N$ with $\bar{c} < \log(2)$, this proves (9.10), and thus completes the proof of the lemma.

There remains to justify (9.11). In view of Proposition 3.1, the probability that $T_N \geq N^3$ is super-exponentially small. Hence, this event can be discarded, and we can focus on bounding the probability of the event

$$\exists s \leq N^3, x \text{ deep trap s.t. } |X_s - x| \leq 1. \tag{9.12}$$

When at a site x , the walk X spends an exponentially distributed time of parameter $\omega_N(x) \leq \bar{\omega}_N$. As was seen in Lemma 5.2, outside of an event whose probability is super-exponentially small, we have $\bar{\omega}_N \leq e^{N^{3/4}}$. It thus follows that outside of an event whose probability is super-exponentially small, the number of sites visited by the walk up to time N^3 is bounded by $e^{N^{4/5}}$. Indeed, if $(\mathbf{e}_k)_{k \in \mathbb{N}}$ are independent random variables of parameter $e^{N^{3/4}}$, then a standard large deviation estimate shows that the probability of the event

$$\sum_{k=1}^{e^{N^{4/5}}} \mathbf{e}_k \leq N^3$$

decays super-exponentially fast with N . As a consequence, outside of an event whose $\overline{\mathbb{P}}_N$ -probability is super-exponentially small, the walk does not discover more than $(N + 1)e^{N^{4/5}} \leq e^{N^{5/6}}$ sites up to time N^3 . But we know from Proposition 4.1 that under $\overline{\mathbb{P}}_N$, the sequence of depths of newly discovered traps is i.i.d. As a consequence, the probability that a deep trap is found among the $e^{N^{5/6}}$ first discovered sites is bounded by

$$e^{N^{5/6}} \mathbb{P}[0 \text{ is a deep trap}] \sim \frac{e^{N^{5/6}}}{\delta^\alpha \mathbf{d}_N},$$

see (6.4). Recalling that $\log(\mathbf{d}_N) \sim \log(\mathbf{t}_N)$, we obtain (9.11), and thus complete the proof. \square

With the two lemmas above, we can now control the expectation of the right-hand side of (9.8).

Proposition 9.7 *For any $\varepsilon > 0$ and any N large enough, if $\|h_N\|_\infty \leq 1$, then*

$$\begin{aligned} & \mathbb{E} \left[\mathbf{P}_u^{\tau_N} [\tau_{N, X_0} \geq \delta B_N] \mathbf{E}_u^{\tau_N} [\tilde{T}_N^M(1)] \mathbf{E}_u^{\tau_N} [h_N(\tau_N(0)) \mid \tau_{N, X_0} \geq \delta B_N] \right] \\ &= \frac{\mathbf{t}_N}{\mathbf{d}_N} (\mathbb{E} [h_N(\tau) \mid \tau_{N, 0} \geq \delta B_N] \pm \varepsilon). \end{aligned} \tag{9.13}$$

Proof Under the expectation on the left-hand side of (9.13) appears a product of three terms, which for convenience we rewrite as $\mathbf{X}_N \mathbf{Y}_N \mathbf{Z}_N$, with obvious identifications. We first show that

$$\mathbb{E}[\mathbf{X}_N \mathbf{Y}_N \mathbf{Z}_N] = (1 \pm \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1} \mathbb{E}[\mathbf{Y}_N \mathbf{Z}_N] \pm 2e^{-N}. \tag{9.14}$$

Let \mathfrak{E}_N be the event

$$\mathbf{X}_N = (1 \pm \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1},$$

and \mathfrak{E}_N^c be the complementary event. We decompose $\mathbb{E}[\mathbf{X}_N \mathbf{Y}_N \mathbf{Z}_N]$ as

$$\mathbb{E}[\mathbf{X}_N \mathbf{Y}_N \mathbf{Z}_N, \mathfrak{E}_N] + \mathbb{E}[\mathbf{X}_N \mathbf{Y}_N \mathbf{Z}_N, \mathfrak{E}_N^c].$$

Since $\mathbf{X}_N, \mathbf{Z}_N \leq 1$, while $\mathbf{Y}_N \leq M \mathbf{t}_N$ and \mathbf{t}_N grows exponentially with N , the second term in the above sum is smaller than e^{-N} by Lemma 9.5. For the first term, the definition of \mathfrak{E}_N implies that

$$\mathbb{E}[\mathbf{X}_N \mathbf{Y}_N \mathbf{Z}_N, \mathfrak{E}_N] = (1 \pm \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1} \mathbb{E}[\mathbf{Y}_N \mathbf{Z}_N, \mathfrak{E}_N].$$

Reasoning as above, we can show that

$$(1 + \varepsilon) \delta^{-\alpha} \mathbf{d}_N^{-1} \mathbb{E}[\mathbf{Y}_N \mathbf{Z}_N, \mathfrak{E}_N^c] \leq e^{-N},$$

so that

$$\mathbb{E}[X_N Y_N Z_N, \mathfrak{E}_N] = (1 \pm \varepsilon) \delta^{-\alpha} d_N^{-1} \mathbb{E}[Y_N Z_N] \pm e^{-N},$$

and this proves (9.14).

Let us now see how a similar reasoning enables to show that

$$\mathbb{E}[Y_N Z_N] = \delta^\alpha t_N (\mathbb{E}[Z_N] \pm \varepsilon). \tag{9.15}$$

Define the event \mathfrak{F}_N as

$$Y_N = (1 \pm \varepsilon) \delta^\alpha t_N.$$

We decompose $\mathbb{E}[Y_N Z_N]$ as

$$\mathbb{E}[Y_N Z_N, \mathfrak{F}_N] + \mathbb{E}[Y_N Z_N, \mathfrak{F}_N^c] = (1 \pm \varepsilon) \delta^\alpha t_N \mathbb{E}[Z_N, \mathfrak{F}_N] + \mathbb{E}[Y_N Z_N, \mathfrak{F}_N^c].$$

Since $Y_N \leq M t_N$ and $Z_N \leq 1$, Lemma 9.6 ensures that

$$0 \leq \mathbb{E}[Y_N Z_N, \mathfrak{F}_N^c] \leq M t_N \mathbb{P}[\mathfrak{F}_N^c] \leq \varepsilon M t_N.$$

On the other hand,

$$\mathbb{E}[Z_N, \mathfrak{F}_N] = \mathbb{E}[Z_N] - \mathbb{E}[Z_N, \mathfrak{F}_N^c]$$

with

$$0 \leq \mathbb{E}[Z_N, \mathfrak{F}_N^c] \leq \varepsilon.$$

To sum up, we have shown that for any $\varepsilon > 0$ and any N large enough,

$$\mathbb{E}[Y_N Z_N] = (1 \pm \varepsilon) \delta^\alpha t_N (\mathbb{E}[Z_N] \pm \varepsilon) \pm \varepsilon M t_N.$$

Recalling that $Z_N \leq 1$, we obtain (9.15) by suitably tuning ε . Combining (9.14) and (9.15) yields

$$\mathbb{E}[X_N Y_N Z_N] = (1 \pm \varepsilon) \frac{t_N}{d_N} (\mathbb{E}[Z_N] \pm \varepsilon) \pm e^{-N}.$$

Since $Z_N \leq 1$ and $\log(d_N/t_N) = o(N)$, this completes the proof as long as we can show that

$$\mathbb{E}[Z_N] = \mathbb{E}[h_N(\tau) \mid \tau_{N,0} \geq \delta B_N] \pm \varepsilon. \tag{9.16}$$

We have

$$\mathbb{E}[Z_N] = \mathbb{E} \left[\frac{\mathbf{E}_u^{\tau_N} [h_N(\tau_N(0)) \mathbf{1}_{\tau_{N,X_0} \geq \delta B_N}]}{\mathbf{P}_u^{\tau_N} [\tau_{N,X_0} \geq \delta B_N]} \right],$$

where the fraction in the right-hand side above is understood to be 1 when the probability in the denominator is 0. We have seen in Lemma 9.5 (used with (6.4)) that with probability tending to 1 as N tends to infinity,

$$\mathbf{P}_u^{\tau_N} [\tau_{N,X_0} \geq \delta B_N] = (1 \pm \varepsilon) \mathbb{P}[\tau_{N,0} \geq \delta B_N],$$

while

$$\mathbb{E} \mathbf{E}_u^{\tau_N} [h_N(\tau_N(0)) \mathbf{1}_{\tau_{N,X_0} \geq \delta B_N}] = \mathbb{E} [h_N(\tau) \mathbf{1}_{\tau_{N,0} \geq \delta B_N}].$$

Equation (9.16) follows from these observations, and this finishes the proof. □

We now consider the left-hand side of (9.8), and start with the following lemma.

Lemma 9.8 *Let \mathcal{D}_N^M be the event*

$$X \text{ discovers a (previously undiscovered) deep trap during the time interval } (T_N^M(1), \tilde{T}_N^M(1)] \tag{9.17}$$

There exists $c > 0$ such that for any M ,

$$\overline{\mathbb{P}}_N [\mathcal{D}_N^M] \leq e^{-cN}.$$

Proof Note first that the difference $\tilde{T}_N^M(1) - T_N^M(1)$ consists in the sum of the random variable $\tilde{\epsilon}_N(1)$ (exponentially distributed with mean N^2), and of a random variable distributed as T_N appearing in Proposition 3.1. By part (2) of this Proposition, we thus know that outside of an event whose probability decays exponentially with N , we have

$$\tilde{T}_N^M(1) - T_N^M(1) \leq N^3.$$

It is thus sufficient to prove the claim with the time interval $(T_N^M(1), \tilde{T}_N^M(1)]$ replaced by $(T_N^M(1), T_N^M(1) + N^3]$. What we need to do then is almost the same as what we proved in the end of the proof of Lemma 9.6. Namely, the argument there ensures that outside of an event whose probability is super-exponentially small, the walk does not discover more than $e^{N^{5/6}}$ sites during this time interval. But we know from Proposition 4.1 that under $\overline{\mathbb{P}}_N$, the sequence of depths of newly discovered traps is i.i.d. As a consequence, the probability that a deep trap is found in no more than $e^{N^{5/6}}$ newly discovered sites is bounded by

$$e^{N^{5/6}} \mathbb{P}[0 \text{ is a deep trap}] \sim \frac{e^{N^{5/6}}}{\delta^\alpha \mathbf{d}_N},$$

see (6.4). Since \mathbf{d}_N grows exponentially with N , this finishes the proof. □

We consider the total time spent at site $x_N^{(\delta)}(1)$ from the moment of discovery $T_N^{(\delta)}(1)$ up to time $T_N^{(\delta)}(1) + \tilde{e}_N(1)$, that is,

$$l_N^{(\delta)} = \int_{T_N^{(\delta)}(1)}^{T_N^{(\delta)}(1) + \tilde{e}_N(1)} \mathbf{1}_{X_s = x_N^{(\delta)}(1)} \, ds. \tag{9.18}$$

The next proposition starts the computation of the expectation of the left-hand side of (9.8).

Proposition 9.9 *There exists $c > 0$ such that for any M and any N large enough, if $\|h_N\|_\infty \leq 1$, then*

$$\mathbb{E}_N \left[\int_0^{\tilde{T}_N^M(1)} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} \, ds \right] = \mathbb{E}_N \left[h_N(\tau_N^{(\delta)}(1)) l_N^{(\delta)}, T_N^{(\delta)}(1) \leq Mt_N \right] \pm e^{-cN}.$$

Proof Note that in the integral

$$\int_0^{\tilde{T}_N^M(1)} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} \, ds,$$

the interval of integration can be replaced by $[T_N^M(1), \tilde{T}_N^M(1)]$, since the walk does not discover any deep trap before $T_N^M(1)$. Since we assume $\|h_N\|_\infty \leq 1$, the integral is bounded by $\tilde{T}_N^M(1) - T_N^M(1)$, which for short we simply write Δ_N^M .

Our first step is to estimate the difference

$$\left| \mathbf{E}_u^{\tau_N} \left[\int_0^{\tilde{T}_N^M(1)} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} \, ds \right] - \mathbf{E}_u^{\tau_N} \left[\int_{T_N^M(1)}^{\tilde{T}_N^M(1)} h_N(\tau_N^{(\delta)}(1)) \mathbf{1}_{X_s = x_N^{(\delta)}(1)} \, ds, T_N^{(\delta)}(1) \leq Mt_N \right] \right|. \tag{9.19}$$

In words, the second integral counts the time spent by the walk only on the first deep trap discovered, and only if this deep trap is discovered before time Mt_N . The difference in (9.19) is thus bounded by

$$\mathbf{E}_u^{\tau_N} \left[\Delta_N^M, \mathfrak{D}_N^M \right], \tag{9.20}$$

where \mathfrak{D}_N^M is the event defined in (9.17). The \mathbb{E} -expectation of this term is bounded by

$$N^3 \overline{\mathbb{P}}_N \left[\mathfrak{D}_N^M \right] + \overline{\mathbb{E}}_N \left[\Delta_N^M, \Delta_N^M \geq N^3 \right].$$

The first term of this sum is exponentially small in N by Lemma 9.8. So is also the second term, since $\Delta_N^M = \tilde{e}_N(1) + \mathbf{T}_N \circ \Theta_{T_N^M(1) + \tilde{e}_N(1)}$ and $\tilde{e}_N(1)$ is an exponential random variable with mean N^2 , while $\mathbf{T}_N - N$ is stochastically dominated by an exponential random variable with mean N by Proposition 3.1. We have thus shown that there exists $c > 0$ such that for any N large enough,

$$\begin{aligned} & \overline{\mathbb{E}}_N \left[\int_0^{\tilde{T}_N^M(1)} h_N(\tau_N(s)) \mathbf{1}_{\tau_N, X_s \geq \delta B_N} ds \right] \\ &= \overline{\mathbb{E}}_N \left[\int_{T_N^M(1)}^{\tilde{T}_N^M(1)} h_N(\tau_N^{(\delta)}(1)) \mathbf{1}_{X_s = x_N^{(\delta)}(1)} ds, T_N^{(\delta)}(1) \leq M \mathbf{t}_N \right] \pm e^{-cN}. \end{aligned} \tag{9.21}$$

On the event $T_N^{(\delta)}(1) \leq M \mathbf{t}_N$, we have $T_N^M(1) = T_N^{(\delta)}(1)$. By the definition of $l_N^{(\delta)}$ (see (9.18)), on this event, we have

$$\int_{T_N^{(\delta)}(1)}^{T_N^{(\delta)}(1) + \tilde{e}_N(1)} h_N(\tau_N^{(\delta)}(1)) \mathbf{1}_{X_s = x_N^{(\delta)}(1)} ds = h_N(\tau_N^{(\delta)}(1)) l_N^{(\delta)}. \tag{9.22}$$

We now wish to show that for some $c > 0$ and N large enough,

$$\overline{\mathbb{E}}_N \left[\int_{T_N^{(\delta)}(1) + \tilde{e}_N(1)}^{\tilde{T}_N^M(1)} h_N(\tau_N^{(\delta)}(1)) \mathbf{1}_{X_s = x_N^{(\delta)}(1)} ds, T_N^{(\delta)}(1) \leq M \mathbf{t}_N \right] \leq e^{-cN}. \tag{9.23}$$

Since $\|h_N\|_\infty \leq 1$, we may as well show that

$$\overline{\mathbb{E}}_N \left[\int_{T_N^{(\delta)}(1) + \tilde{e}_N(1)}^{\tilde{T}_N^M(1)} \mathbf{1}_{X_s = x_N^{(\delta)}(1)} ds, T_N^{(\delta)}(1) \leq M \mathbf{t}_N \right] \leq e^{-cN}.$$

In order to do so, let us define \mathfrak{D}'_N the event

$$\tilde{e}_N(1) < N \quad \text{or} \quad \Delta_N^M \geq N^3.$$

Arguing as above, we see that the probability of this event is exponentially small in N . Proceeding as in the analysis of the term (9.20), it then follows that

$$\overline{\mathbb{E}}_N \left[\int_{T_N^{(\delta)}(1) + \tilde{e}_N(1)}^{\tilde{T}_N^M(1)} \mathbf{1}_{X_s = x_N^{(\delta)}(1)} \, ds, \quad T_N^{(\delta)}(1) \leq M \mathbf{t}_N, \quad \mathfrak{D}'_N \right] \leq e^{-cN}.$$

In order to prove (9.23), it thus suffices to show that

$$\overline{\mathbb{E}}_N \left[\int_{T_N^{(\delta)}(1) + N}^{T_N^{(\delta)}(1) + N^3} \mathbf{1}_{X_s = x_N^{(\delta)}(1)} \, ds \right] \leq e^{-cN}.$$

Recall that as $x_N^{(\delta)}(1)$ is discovered at time $T_N^{(\delta)}(1)$, it must be that $|X_{T_N^{(\delta)}(1)} - x| \leq 1$. Hence,

$$\mathbf{E}_{\mathbf{u}}^{\tau_N} \left[\int_{T_N^{(\delta)}(1) + N}^{T_N^{(\delta)}(1) + N^3} \mathbf{1}_{X_s = x_N^{(\delta)}(1)} \, ds \right] \leq \mathbf{E}_{\mathbf{u}}^{\tau_N} \left[\int_{T_N^{(\delta)}(1) + N}^{T_N^{(\delta)}(1) + N^3} \mathbf{1}_{|X_s - X_{T_N^{(\delta)}(1)}| \leq 1} \, ds \right].$$

By the Markov property, the latter integral is equal to

$$\mathbf{E}_{\mathbf{u}}^{\tau_N} \left[\int_N^{N^3} \underbrace{\mathbf{P}_{X_{T_N^{(\delta)}(1)}}^{\tau_N}}_{[|X_s - X_0| \leq 1]} \, ds \right].$$

By Proposition 3.4, the probability underbraced above is exponentially small in N , uniformly over τ_N , $X_{T_N^{(\delta)}(1)}$ and $s \geq N$. This completes the proof of (9.23). Equations (9.21), (9.22) and (9.23) imply the proposition. \square

We can now conclude our analysis of the expectation of the left-hand side of identity (9.8).

Proposition 9.10 *There exists $c > 0$ such that for any M and any N large enough, if $\|h_N\|_\infty \leq 1$, then*

$$\overline{\mathbb{E}}_N \left[h_N(\tau_N^{(\delta)}(1)) l_N^{(\delta)}, \quad T_N^{(\delta)}(1) \leq M \mathbf{t}_N \right] = \overline{\mathbb{E}}_N \left[(h_N G_N)(\tau_N^{(\delta)}(1)), \quad \mathcal{E}_N^M \right] \pm e^{-cN},$$

where we recall that the event \mathcal{E}_N^M was defined in (9.2).

Proof First, note that

$$\mathbb{E}_N \left[h_N(\tau_N^{(\delta)}(1)) l_N^{(\delta)}, T_N^{(\delta)}(1) \leq M t_N \right] = \mathbb{E}_N \left[h_N(\tau_N^{(\delta)}(1)) l_N^{(\delta)}, \mathcal{E}_N^M \right] \pm e^{-cN}. \tag{9.24}$$

Indeed, the quantities under the two expectations above are equal unless the deep trap $x_N^{(\delta)}(1)$ is visited in the time interval $(T_N^{(\delta)}(1) + N, T_N^{(\delta)}(1) + \tilde{e}_N]$. Hence (9.24) is obtained as in the proof of Proposition 9.9, noting that the probability of this event is exponentially small in N by Proposition 3.4.

Let us write $H_N^{(\delta)}(n)$ for the first time the walk visits the site $x_N^{(\delta)}(n)$, and define

$$\tilde{l}_N^{(\delta)}(n) = \int_{H_N^{(\delta)}(n)}^{H_N^{(\delta)}(n) + \tilde{e}_N(n)} \mathbf{1}_{X_s = x_N^{(\delta)}(n)} \, ds. \tag{9.25}$$

By a similar reasoning, we have

$$\mathbb{E}_N \left[h_N(\tau_N^{(\delta)}(1)) l_N^{(\delta)}, \mathcal{E}_N^M \right] = \mathbb{E}_N \left[h_N(\tau_N^{(\delta)}(1)) \tilde{l}_N^{(\delta)}(1), \mathcal{E}_N^M \right] \pm e^{-cN}. \tag{9.26}$$

Indeed, the quantities under the two expectations above are equal unless the deep trap $x_N^{(\delta)}(1)$ is visited during the time interval $(T_N^{(\delta)}(1) + \tilde{e}_N(1); H_N^{(\delta)}(1) + \tilde{e}_N(1)]$. On the event \mathcal{E}_N^M , we have that the length of this interval is smaller than N . Moreover, outside of an event whose probability is exponentially small, we have $\tilde{e}_N(1) \geq N$. So we can argue as above and obtain (9.26).

Let $e_N^{(\delta)}(n)$ be such that

$$\tilde{l}_N^{(\delta)}(n) = G_N(\tau_N^{(\delta)}(n)) e_N^{(\delta)}(n). \tag{9.27}$$

Under the measure $\mathbf{P}_u^{\tau_N}$ and conditionally on $x_N^{(\delta)}(1) = x$, the quantity $\tilde{l}_N^{(\delta)}(1)$ is independent of $(X_t)_{t \leq H_N^{(\delta)}(1)}$. Moreover, it is the total time spent on x by the walk X starting at x and with a killing parameter equal to $1/N^2$. In particular, $\tilde{l}_N^{(\delta)}(1)$ is an exponential random variable with mean $G_N(\tau_N^{(\delta)}(1))$. In other words, we thus see that under the measure $\mathbf{P}_u^{\tau_N}$ and conditionally on $x_N^{(\delta)}(1) = x$, the quantity $e_N^{(\delta)}(1)$ is independent of $(X_t)_{t \leq H_N^{(\delta)}(1)}$ and follows an exponential distribution with parameter 1. Since this does not depend on x , we have thus shown that under the measure $\mathbf{P}_u^{\tau_N}$, the quantity $e_N^{(\delta)}(1)$ is independent of $(X_t)_{t \leq H_N^{(\delta)}(1)}$ and follows an exponential distribution with parameter 1. In particular, (and since \mathcal{E}_N^M is measurable with respect to $(X_t)_{t \leq H_N^{(\delta)}(1)}$), we have

$$\begin{aligned} \mathbf{E}_u^{\tau_N} \left[h_N(\tau_N^{(\delta)}(1)) \tilde{l}_N^{(\delta)}(1), \mathcal{E}_N^M \right] &= \mathbf{E}_u^{\tau_N} \left[(h_N G_N)(\tau_N^{(\delta)}(1)) \tilde{e}_N^{(\delta)}(1), \mathcal{E}_N^M \right] \\ &= \mathbf{E}_u^{\tau_N} \left[(h_N G_N)(\tau_N^{(\delta)}(1)), \mathcal{E}_N^M \right]. \end{aligned}$$

Taking expectations and using (9.26), we obtain the announced result. □

Proof of Theorem 9.1 The theorem follows by combining the identity (9.8) with Propositions 9.7, 9.9 and 9.10, and recalling that $\log(d_N/t_N) = o(N)$. □

Of course, Theorem 9.1 is truly interesting only if the probability of \mathcal{E}_N^M can be taken arbitrarily close to 1. It follows from Proposition 7.1 that $\bar{\mathbb{P}}_N[T_N^{(\delta)}(1) \leq Mt_N]$ can be taken arbitrarily close to 1 by choosing M large enough. Our goal is now to prove that $\mathcal{H}_N^{(\delta)}(n)$ occurs with high probability.

Proposition 9.11 *For any $n \in \mathbb{N}$,*

$$\bar{\mathbb{P}}_N \left[\mathcal{H}_N^{(\delta)}(n) \right] \xrightarrow{N \rightarrow \infty} 1.$$

Let us write $x \approx y$ when $x, y \in V_N$ are neighbours or second neighbours. The proof of the proposition relies on the following lemma.

Lemma 9.12 *For any $n \in \mathbb{N}$,*

$$\bar{\mathbb{P}}_N \left[\max_{z \approx x_N^{(\delta)}(n)} E_z \leq 2\sqrt{\log N} \right] \xrightarrow{N \rightarrow \infty} 1.$$

Proof We introduce some terminology (slightly adapted from [37]). For any $z \approx 0$, we say that $x \in V_N$ is *z-atypical* if it is a deep trap (that is, $\tau_{N,x} \geq \delta B_N$) and moreover, $E_{x+z} > 2\sqrt{\log N}$. The lemma can be rephrased as stating that

$$\bar{\mathbb{P}}_N \left[x_N^{(\delta)}(n) \text{ is } z\text{-atypical for some } z \approx 0 \right]$$

tends to 0 as N tends to infinity.

We say that $x \in V_N$ is *z-uncommon* if it is *z-atypical*, or if $(x - z)$ is *z-atypical*. Finally, for a subset $\Gamma \subseteq V_N$, we say that x is *z-uncommon regardless of Γ* if one can infer that x is *z-uncommon* without considering sites inside Γ , i.e. if one of the two following conditions occur:

x is *z-atypical* and $\{x, x+z\} \cap \Gamma = \emptyset$, or $(x-z)$ is *z-atypical* and $\{x-z, x\} \cap \Gamma = \emptyset$.

We learn from [37, Lemma 7.2] that if $x_N^{(\delta)}(n)$ is *z-atypical*, then there exists $k \leq r_N^{(\delta)}(n)$ such that x_k is *z-uncommon regardless of Γ* (recall that x_1, x_2, \dots denotes the exploration process introduced in Sect. 4). As was seen in the proof of

Proposition 7.1, the random variable $\mathbf{d}_N^{-1} r_N^{(\delta)}(n)$ converges in distribution under $\bar{\mathbb{P}}_N$, hence the probability

$$\bar{\mathbb{P}}_N \left[r_N^{(\delta)}(n) \leq C_r \mathbf{d}_N \right] \tag{9.28}$$

can be made as close to 1 as desired by choosing C_r sufficiently large. Moreover,

$$\begin{aligned} & \bar{\mathbb{P}}_N \left[x_N^{(\delta)}(n) \text{ is } z\text{-atypical for some } z \approx 0, r_N^{(\delta)}(n) \leq C_r \right] \\ & \leq \sum_{z \approx 0} \sum_{k=1}^{C_r \mathbf{d}_N} \underbrace{\bar{\mathbb{P}}_N \left[x_k \text{ is } z\text{-uncommon regardless of } \{x_1, \dots, x_{k-1}\} \right]}_{\text{probability}}. \end{aligned} \tag{9.29}$$

As was observed in the proof of [37, Proposition 7.1], the invariance of \mathbb{P} under translations implies that the probability underbraced above is bounded by

$$\mathbb{P}[0 \text{ is } z\text{-uncommon}],$$

which in turn is bounded by

$$2 \bar{\mathbb{P}}_N [0 \text{ is } z\text{-atypical}] \leq 2 \bar{\mathbb{P}}_N [\tau_{N,0} \geq \delta B_N] \bar{\mathbb{P}}_N [E_z > 2\sqrt{\log N}].$$

Using (6.4) and (6.1), we obtain that for N large enough, the probability on the left-hand side of (9.29) is bounded by

$$8C_r N^2 \delta^{-\alpha} \frac{1}{2\sqrt{2\pi \log N}} e^{-(2\sqrt{\log N})^2/2},$$

which tends to 0 as N tends to infinity. □

Proof of Proposition 9.11 Let us condition on the event that the position of the walk at time $T_N^{(\delta)}(n)$ is $x \in V_n$. Note that in this case, $x_N^{(\delta)}(n)$ must be a neighbour of x . On this event, the $\mathbf{P}_u^{T_N}$ -probability that the next jump of the walk is from x to $x_N^{(\delta)}(n)$ is given by

$$\frac{\exp \left(a_N E_{x_N^{(\delta)}(n)} \right)}{\sum_{y \sim x} \exp \left(a_N E_y \right)} = \frac{\exp \left(a_N E_{x_N^{(\delta)}(n)} \right)}{\exp \left(a_N E_{x_N^{(\delta)}(n)} \right) + \sum_{y \sim x, y \neq x_N^{(\delta)}(n)} \exp \left(a_N E_y \right)}.$$

Recall that $a_N \geq 1$ and $a_N \leq \bar{a} \sqrt{2 \log N}$. Since $x_N^{(\delta)}(n)$ is a deep trap, the numerator above is larger than $\exp(\sqrt{2\bar{c}N}(1+o(1)))$, while the sum appearing in the denominator has no more than N terms, each of them being smaller than $\exp(2\sqrt{2\bar{a} \log N})$ on the event that

$$\max_{z \approx x_N^{(\delta)}(n)} E_z \leq 2\sqrt{\log N}.$$

Using Lemma 9.12, we can thus conclude that with probability tending to 1, the walk jumps to $x_N^{(\delta)}(n)$ right after having discovered it. The total time spent on any site is an exponential random variable whose parameter is at least N , so this jump occurs fast enough to ensure that Proposition 9.11 holds. \square

10 The Green function at the origin

Let us write $\mathbb{P}^\circ = \mathbb{P}[\cdot \mid \tau_{N,0} \geq \delta B_N]$, and $\bar{\mathbb{P}}_N^\circ = \mathbb{P}^\circ \mathbf{P}_0^{\tau_N}$. The purpose of this section is to prove the following result.

Theorem 10.1 *Under the measure \mathbb{P}° , the random variable $N^2 \phi(a_N)^2 G_N(\tau_N)$ converges to 1 in probability, where we recall that ϕ is the function introduced in (2.5).*

The idea of the proof consists in (1) computing the expected time the walk spends on the origin before exiting its 1-neighbourhood, and (2) showing that once the walk has exited the 1-neighbourhood of the origin, it will not come back to it sufficiently fast to be accounted in $G_N(\tau_N)$. The most technical part is (2), which is achieved in two main steps. In the first step (Proposition 10.6), we show that there exists $\zeta > 0$ such that with probability tending to 1, the walk does not come back to the origin up to time N^ζ . In the second step, we rely on Proposition 3.5 to justify that the walk will not come back to the origin soon enough after N^ζ . This is slightly delicate, since the statement in Proposition 3.5 is averaged over \mathbb{P} , while we consider here an average over \mathbb{P}° .

For any $n \in \mathbb{N}$, we let $H_n = \inf\{t \geq 0 : |X_t - X_0| = n\}$.

Lemma 10.2 *Under $\mathbf{P}_x^{\tau_N}$, the total time spent at the initial position up to H_2 :*

$$\int_0^{H_2} \mathbf{1}_{X_s = X_0} \, ds$$

follows an exponential distribution with parameter

$$e^{a_N E_x} \sum_{y \sim x} e^{a_N E_y} \frac{\sum_{y \sim x} e^{a_N E_y} \sum_{z \sim y, z \neq x} e^{a_N E_z}}{\sum_{y \sim x} e^{a_N E_y} (e^{a_N E_x} + \sum_{z \sim y, z \neq x} e^{a_N E_z})}. \tag{10.1}$$

Proof Under $\mathbf{P}_x^{\tau_N}$, the walk stays at the origin an exponential time of parameter

$$e^{a_N E_x} \sum_{y \sim x} e^{a_N E_y}.$$

Then it jumps to some $y \sim x$ with probability proportional to $e^{a_N E_y}$. The fraction in (10.1) is thus the probability that the walk hits a point at distance 2 from x before returning to x . The result then follows from these observations. \square

Proposition 10.3 Recall that we assume $\bar{a} < 1/20$. For any $\varepsilon > 0$, we have

$$\mathbb{P} \left[\sum_{x \sim 0} e^{a_N E_x} \sum_{y \sim x, y \neq 0} e^{a_N E_y} = (1 \pm \varepsilon) N^2 \phi(a_N)^2 \right] = 1 - o(N^{-2}). \tag{10.2}$$

Remark 10.4 For the purpose of this section, it would be sufficient to show that the probability in the left-hand side of (10.2) tends to 1 as N tends to infinity. The quantitative estimate given here will prove important in the next section.

Proof of Proposition 10.3 We first prove that for any $\varepsilon > 0$,

$$\mathbb{P} \left[\sum_{x \sim 0} e^{a_N E_x} = (1 \pm \varepsilon) N \phi(a_N) \right] = 1 - o(N^{-3}), \tag{10.3}$$

and we do so by a computation of moments. We write $\chi_N(x)$ for $e^{a_N E_x} - \mathbb{E}[e^{a_N E_x}] = e^{a_N E_x} - \phi(a_N)$. For any integer m , we have

$$\begin{aligned} \mathbb{E} \left[\left(\sum_{x \sim 0} \chi_N(x) \right)^{2m} \right] &= \sum_{x_1, \dots, x_{2m} \sim 0} \mathbb{E} [\chi_N(x_1) \cdots \chi_N(x_{2m})] \\ &= \sum_{\substack{k=1 \\ e_i \geq 1}}^{2m} \sum_{e_1 + \dots + e_k = 2m} C_{e_1, \dots, e_k} \sum_{\substack{y_1, \dots, y_k \sim 0 \\ y_i \neq y_j}} \mathbb{E} [\chi_N(y_1)^{e_1} \cdots \chi_N(y_k)^{e_k}]. \end{aligned} \tag{10.4}$$

The last equality is obtained in the following way. For every sequence (x_1, \dots, x_{2m}) , we let k be the cardinality of $\{x_1, \dots, x_{2m}\}$, and write this set as $\{y_1, \dots, y_k\}$, where the y_i 's are pairwise distinct. Then $e_i (\geq 1)$ is the number of occurrences of y_i in the sequence (x_1, \dots, x_{2m}) . It is an interesting combinatorial exercise to see that the coefficient C_{e_1, \dots, e_k} appearing in the formula is the multinomial coefficient associated with (e_1, \dots, e_k) divided by $k!$, but the only important thing for us is that this coefficient does not depend on N . Since $(\chi_N(x))_{x \sim 0}$ are independent and centred random variables, the expectation $\mathbb{E} [\chi_N(y_1)^{e_1} \cdots \chi_N(y_k)^{e_k}]$ vanishes as soon as one of the e_i 's is equal to 1. Hence, up to a constant (depending only on m), the left-hand side of (10.4) is bounded by

$$\sum_{k=1}^m \sum_{\substack{e_1 + \dots + e_k = 2m \\ e_i \geq 2}} \sum_{\substack{y_1, \dots, y_k \sim 0 \\ y_i \neq y_j}} \prod_{i=1}^k |\mathbb{E} [\chi_N(y_i)^{e_i}]|.$$

Up to a constant, the quantity above is bounded by

$$\sum_{k=1}^m \sum_{\substack{e_1 + \dots + e_k = 2m \\ e_i \geq 2}} N^k \prod_{i=1}^k \phi(a_N e_i) \leq 2^m \sum_{k=1}^m \sum_{\substack{e_1 + \dots + e_k = 2m \\ e_i \geq 2}} N^k \exp \left(\frac{a_N^2}{2} \sum_{i=1}^k e_i^2 \right),$$

where we used the fact that $\phi(\lambda) \leq 2e^{\lambda^2/2}$ (see (2.5)). Since the square function is convex and takes value 0 at 0, we have

$$\sum_{i=1}^k e_i^2 \leq \left(\sum_{i=1}^k e_i \right)^2 = 4m^2.$$

We have thus shown that for any m , there exists a constant C such that

$$\mathbb{E} \left[\left(\sum_{x \sim 0} \chi_N(x) \right)^{2m} \right] \leq CN^m \exp \left(2a_N^2 m^2 \right).$$

Choosing $m = 4$ and recalling that $\bar{a} < 1/20$, we obtain

$$\mathbb{E} \left[\left(\sum_{x \sim 0} \chi_N(x) \right)^8 \right] = o(N^5).$$

An application of Chebyshev’s inequality then proves (10.3).

For any $\varepsilon > 0$, we consider the event formed by the conjunction of

$$\sum_{x \sim 0} e^{a_N E_x} = (1 \pm \varepsilon) N \phi(a_N)$$

and for any $x \sim 0$,

$$\sum_{y \sim x, y \neq 0} e^{a_N E_y} = (1 \pm \varepsilon) N \phi(a_N).$$

It follows from (10.3) that this event has probability at least $1 - o(N^{-2})$. On this event, we have

$$\sum_{x \sim 0} e^{a_N E_x} \sum_{y \sim x, y \neq 0} e^{a_N E_y} = (1 \pm \varepsilon)^2 N^2 \phi(a_N)^2,$$

and thus the result is proved. □

Remark 10.5 Although the proof makes it transparent that the condition $\bar{a} < 1/20$ is not really necessary, one can convince oneself that Proposition 10.3 does not hold for every $\bar{a} < 1$.

Proposition 10.6 *Let $\zeta > 0$, and let \mathfrak{A}_N be the event*

$$\inf\{t \geq H_2 : |X_t - X_0| \leq 1\} \geq H_2 + N^\zeta^{-1}, \tag{10.5}$$

Recall that we assume $\bar{a} < 1/20$. If ζ is sufficiently small, then

$$\mathbb{P}_N^\circ [\mathfrak{A}_N] \xrightarrow{N \rightarrow \infty} 1.$$

Remark 10.7 Recall that $|\cdot|$ denotes the Hamming distance on the hypercube. By a slight abuse of notation, we will simply write $|x|$ instead of $|x - 0|$, when $x \in V_N$.

Proof We will first show that with probability tending to 1, the walk starting from time H_2 keeps going away from the origin at least up to distance $N^{1/4}$. We then show that a good proportion of these steps take time at least $N^{-1-5\bar{a}}$, thus justifying that on this event, the walk has not returned to the 1-neighbourhood of the origin up to time $N^{-3/4-5\bar{a}}$. This will prove the proposition since we assume $\bar{a} < 1/20$.

We begin by introducing $(\bar{Y}_n)_{n \geq 2}$ the discrete-time walk that records the successive positions of $(X_t)_{t \geq H_2}$. The indexation is chosen so that \bar{Y}_2 is at distance 2 from the origin (that is, $|\bar{Y}_2| = 2$).

We also introduce a slightly modified version of the exploration process. This new exploration process, that we denote by $\bar{x}_1, \bar{x}_2, \dots$, is obtained from the original one by suppressing all sites belonging to $\{x : |x| \leq 2\}$. Note that each step of \bar{Y} gives rise to a (possibly empty) set of newly discovered sites (for this modified exploration process). For $n \geq 2$, we write $\bar{\mathcal{X}}_{n+1}$ for the set of sites thus discovered by \bar{Y} at (discrete) time n (see Fig. 1). For $n \in \{1, 2\}$, we also define

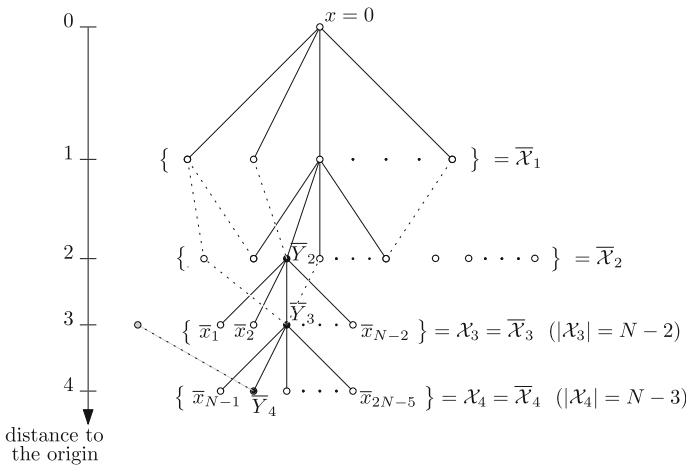


Fig. 1 A schematic representation of a neighbourhood of the origin (on top). All points on one level are at the same distance from the origin. The black dots denote the sites visited by the random walk starting from time H_2 , indexed by $\bar{Y}_2, \bar{Y}_3, \bar{Y}_4$. Although the drawing (with only the solid edges) looks like a tree, note that the further one goes away from the origin, the more there are edges destroying the tree structure, as exemplified by the dotted edges. For instance, any point on level 3 should be connected to 3 vertices on level 2. By construction, $\bar{\mathcal{X}}_3$ contains exactly $N - 2$ sites, all at distance 3 from the origin, and is equal to \mathcal{X}_3 . Note that $\mathcal{X}_4 = \bar{\mathcal{X}}_4$ is a consequence of the fact that in the example, $|\bar{Y}_3| = 3$. Although on the example, since $|\bar{Y}_4| = 4$, we have $\mathcal{X}_5 \subseteq \bar{\mathcal{X}}_5$ (not drawn on the picture), these two sets are not equal, since the grey dot on level 3 belongs to $\bar{\mathcal{X}}_5$ but not to \mathcal{X}_5 (every point of \mathcal{X}_5 being on level 5)

$$\bar{\mathcal{X}}_n = \{x \in V_N : |x| = n\}.$$

Under $\bar{\mathbb{P}}_N^\circ$, the distribution of \bar{Y} up to time n does not depend on $(E_{\bar{x}_i})_{i \in \bar{\mathcal{X}}_{n+1}}$, and therefore the latter is a family of independent random variables distributed as $\mathcal{N}_+(0, 1)$, independent of $(E_{\bar{x}_i})_{i \in \cup_{k \leq n} \bar{\mathcal{X}}_k}$ (this is the same argument as in Proposition 4.1).

Finally, for $n \geq 2$, we let

$$\mathcal{X}_{n+1} = \{x \in V_N : |x| = n + 1 \text{ and } x \sim X_{H_n}\}.$$

In words, to form \mathcal{X}_{n+1} , one waits until the first time the random walk visits a point at distance n from the origin, and then collects all neighbouring points that are at distance $n + 1$ from the origin. The successive sets $\mathcal{X}_3, \mathcal{X}_4, \dots$ can be seen as yet another exploration process, this one being very far from ultimately covering the whole graph. Again, under $\bar{\mathbb{P}}_N^\circ$, the distribution of $(X_t)_{t \leq H_n}$ does not depend on $(E_x)_{x \in \mathcal{X}_{n+1}}$, and the latter is thus a family of independent random variables distributed as $\mathcal{N}_+(0, 1)$, and is independent of $(E_x)_{x \in \cup_{k \leq n} \mathcal{X}_k}$. Note that for $2 \leq n \leq N$, we have $|\mathcal{X}_{n+1}| = N - n$ (see Fig. 1).

Let $\mathfrak{A}_N(n)$ be the event defined to be the conjunction of the event $|\bar{Y}_n| = n$ and of the event

$$\max \left\{ E_x, x \in \bigcup_{1 \leq k \leq n} \bar{\mathcal{X}}_k \right\} \leq 2\sqrt{2 \log N}. \tag{10.6}$$

We now prove by induction on n that if (N is large enough and) $2 \leq n \leq N^{1/4}$, then

$$\bar{\mathbb{P}}_N^\circ [\mathfrak{A}_N(n)] \geq 1 - nN^{5\bar{\alpha}-3/4}. \tag{10.7}$$

We start by checking that such is the case for $n = 2$. The walk always satisfies $|\bar{Y}_2| = 2$, so we only need to bound the probability of the event

$$\max \{E_x, x \in \bar{\mathcal{X}}_1 \cup \bar{\mathcal{X}}_2\} \leq 2\sqrt{2 \log N}.$$

Noting that $|\bar{\mathcal{X}}_1 \cup \bar{\mathcal{X}}_2| = N(N + 1)/2$ and using (5.4), we can bound this probability from below by

$$\left(1 - e^{-(2\sqrt{2 \log N})^2/2}\right)^{N(N+1)/2} = \left(1 - N^{-4}\right)^{N(N+1)/2} = 1 - \frac{1}{2N^2}(1 + o(1)),$$

and this justifies the base case of the induction.

Let $2 \leq n < N^{1/4}$, and assume that (10.7) holds. It suffices to check that

$$\bar{\mathbb{P}}_N^\circ [\mathfrak{A}_N^c(n + 1) \mid \mathfrak{A}_N(n)] \leq N^{5\bar{\alpha}-3/4}, \tag{10.8}$$

where we write $\mathfrak{A}_N^c(n + 1)$ for the complement of $\mathfrak{A}_N(n + 1)$. The probability on the left-hand side above is smaller than the sum of

$$\mathbb{P}_N^\circ \left[\max_{x \in \overline{\mathcal{X}}_{n+1}} E_x > 2\sqrt{2 \log N} \mid \mathfrak{A}_N(n) \right] \tag{10.9}$$

and

$$\mathbb{P}_N^\circ \left[|\overline{Y}_{n+1}| \neq n + 1 \mid \mathfrak{A}_N(n) \right]. \tag{10.10}$$

Since $(E_x)_{x \in \overline{\mathcal{X}}_{n+1}}$ is independent of $\mathfrak{A}_N(n)$, we can proceed as on the base case of this induction and show that the probability in (10.9) is $O(N^{-3})$. We now consider the probability in (10.10). Recall that \overline{Y} chooses to jump to a neighbouring site x with probability proportional to $e^{a_N E_x}$. On the event $|\overline{Y}_n| = n$, \overline{Y}_n has $N - n$ neighbours at level $(n + 1)$ (the elements of \mathcal{X}_{n+1}), and n other neighbours belonging to $\bigcup_{k \leq n} \overline{\mathcal{X}}_k$. Since the energy on any site is always positive, on the event $\mathfrak{A}_N(n)$, the probability that $|\overline{Y}_{n+1}| = n + 1$ is at least

$$\frac{N - n}{N - n + ne^{2a_N \sqrt{2 \log N}}}. \tag{10.11}$$

Since we assume $n < N^{1/4}$ and $a_N \leq \bar{a} \sqrt{2 \log N}$, the quantity above is larger than

$$\frac{N/2}{N/2 + N^{1/4+4\bar{a}}} = 1 - 2N^{4\bar{a}-3/4}(1 + o(1)). \tag{10.12}$$

This justifies (10.8), and thus completes the proof of (10.7).

It follows from (10.7) that with probability tending to 1, the event $\mathfrak{A}_N(N^{1/4})$ is realized. We now explain why the walk cannot run its first $N^{1/4}$ steps too fast.

First, we recall that under \mathbb{P}_N° , the values $(E_x)_{x \in \mathcal{X}_3}, (E_x)_{x \in \mathcal{X}_4}, \dots, (E_x)_{x \in \mathcal{X}_N}$ form a family of independent random variables distributed as $\mathcal{N}_+(0, 1)$. Since $|\mathcal{X}_{n+1}| \leq N$ and $\mathbb{E}[e^{a_N E_x}] = \phi(a_N) \leq 2e^{a_N^2/2}$, Chebyshev’s inequality guarantees that if $3 \leq k \leq N$, then

$$\mathbb{P}_N^\circ \left[\sum_{x \in \mathcal{X}_k} e^{a_N E_x} > 4N e^{a_N^2/2} \right] \leq \frac{1}{2}.$$

By independence, a classical large deviation estimate guarantees that the \mathbb{P}_N° -probability that

$$\left| \left\{ k \leq N^{1/4} : \sum_{x \in \mathcal{X}_k} e^{a_N E_x} \leq 4N e^{a_N^2/2} \right\} \right| \geq \frac{N^{1/4}}{4} \tag{10.13}$$

tends to 1 as N tends to infinity. Let us write \mathfrak{A}'_N for the event that both $\mathfrak{A}_N(N^{1/4})$ and the event displayed in (10.13) are satisfied. By (10.7), we thus have

$$\mathbb{P}^\circ_N [\mathfrak{A}'_N] \xrightarrow[N \rightarrow \infty]{} 1. \tag{10.14}$$

Let $\gamma = (\gamma_n)_{2 \leq n \leq N^{1/4}}$ be a path. We write $\bar{Y} = \gamma$ to denote the event that for any n , $2 \leq n \leq N^{1/4}$, we have $\bar{Y}_n = \gamma_n$. In a given environment τ_N , the event \mathfrak{A}'_N depends only on $(\bar{Y}_n)_{2 \leq n \leq N^{1/4}}$. Let $\Gamma(\tau_N)$ be the set of paths γ such that in the environment τ_N and on $Y = \gamma$, the event \mathfrak{A}'_N is realized.

We now fix some $\gamma \in \Gamma(\tau_N)$. Conditionally on $Y = \gamma$, the waiting times of the continuous-time walk X on the successive sites $(\gamma_n)_{2 \leq n \leq N^{1/4}}$ are independent exponential random variables with respective parameter

$$e^{a_N E_{\gamma_n}} \sum_{x \sim \gamma_n} e^{a_N E_x}. \tag{10.15}$$

On $Y = \gamma$, the event \mathfrak{A}'_N is realized, and in particular:

- the set $\{x : x \sim \gamma_n\}$ is partitioned into the $N - n$ sites that belong to \mathcal{X}_{n+1} on one hand, and the $n \leq N^{1/4}$ sites that belong to some $\bar{\mathcal{X}}_k$ for some $k \leq n$ on the other;
- the site γ_n itself belongs to $\bar{\mathcal{X}}_k$ for some $k \leq n$;
- The events (10.6), (10.13) hold, and γ does not visit the origin.

These observations enable to bound the parameter in (10.15) by

$$e^{2a_N \sqrt{2 \log N}} \left(\sum_{x \in \mathcal{X}_{n+1}} e^{a_N E_x} + N^{1/4} e^{2a_N \sqrt{2 \log N}} \right),$$

and for at least $N^{1/4}/4$ of these n 's, the latter is smaller than

$$e^{2a_N \sqrt{2 \log N}} \left(4N e^{a_N^2/2} + N^{1/4} e^{2a_N \sqrt{2 \log N}} \right) \leq N^{4\bar{a}} \left(4N^{1+\bar{a}^2} + N^{1/4+4\bar{a}} \right).$$

To sum up, under the measure $\mathbf{P}_0^{\tau_N}$ and conditionally on the event $Y = \gamma$, the total time it takes for the continuous-time walk X to travel through γ stochastically dominates a sum of $N^{1/4}/4$ independent exponential random variables of parameter bounded by $5N^{1+4\bar{a}+\bar{a}^2}$. With probability tending to 1 (uniformly over τ_N and $\gamma \in \Gamma(\tau_N)$), this sum is larger than $N^{-3/4+5\bar{a}}$. Since we assume $\bar{a} < 1/20$, there exists $\zeta > 0$ such that $-3/4 + 5\bar{a} = -1 + \zeta$. In particular, we have shown that, uniformly over τ_N ,

$$\inf_{\gamma \in \Gamma(\tau_N)} \mathbf{P}_0^{\tau_N} [\mathfrak{A}_N | Y = \gamma] \xrightarrow[N \rightarrow \infty]{} 1. \tag{10.16}$$

Moreover,

$$\begin{aligned} \mathbf{P}_0^{\tau_N} [\mathfrak{A}_N \cap \mathfrak{A}'_N] &= \sum_{\gamma \in \Gamma(\tau_N)} \mathbf{P}_0^{\tau_N} [\mathfrak{A}_N, Y = \gamma] \\ &= \sum_{\gamma \in \Gamma(\tau_N)} \mathbf{P}_0^{\tau_N} [\mathfrak{A}_N | Y = \gamma] \mathbf{P}_0^{\tau_N} [Y = \gamma]. \end{aligned}$$

From (10.16), it thus follows that for any N large enough, uniformly over τ_N ,

$$\begin{aligned} \mathbf{P}_0^{\tau_N} [\mathfrak{A}_N \cap \mathfrak{A}'_N] &= (1 + o(1)) \sum_{\gamma \in \Gamma(\tau_N)} \mathbf{P}_0^{\tau_N} [Y = \gamma] \\ &= (1 + o(1)) \mathbf{P}_0^{\tau_N} [\mathfrak{A}'_N]. \end{aligned}$$

Integrating with respect to \mathbb{P}° and using (10.14), we obtain the desired result. □

Remark 10.8 There are many ways to improve the proof of Proposition 10.6 so that it covers higher values of \bar{a} . Yet, we now explain why a simple optimization of exponents cannot cover every $\bar{a} < 1$. Let ξ be an exponent such that with probability tending to 1, the event $|\bar{Y}_{N^\xi}| = N^\xi$ occurs with probability tending to 1. We have seen in the proof of Proposition 10.6 that for \bar{a} small enough, one can take $\xi = 1/4$. Yet, as \bar{a} is taken closer and closer to 1 (and fixing $a_N = \bar{a}\sqrt{2 \log N}$), the exponent ξ must approach 0, while the time spent on a site during the descent is an exponential random variable with parameter of order at least $N\phi(a_N) \sim N^{1+\bar{a}^2}$. That is, the total time spent on the full descent is of order no more than $N^{-\bar{\zeta}}$ with $\bar{\zeta}$ approaching 2 as \bar{a} is taken closer and closer to 1.

Lemma 10.9 *Let $\zeta \in (0, 1)$. There exists a measurable $\Omega'_N \subseteq \Omega_N$ such that $\mathbb{P}[\Omega'_N]$ tends to 1 as N tends to infinity, and moreover, for any $\tau_N \in \Omega'_N$,*

$$\forall x \approx 0, \mathbf{P}_x^{\tau_N} \left[\exists t : N^{\zeta-1} \leq t \leq N^3 : |X_t| \leq 1 \right] \leq \exp(-N^\zeta/2). \tag{10.17}$$

Proof Proposition 3.5 (or more precisely, inequality (3.3)) ensures that for any $x \in V_N$,

$$\mathbb{E} \mathbf{E}_x^{\tau_N} \left[\int_{N^{\zeta-1}}^{N^3+1} \mathbf{1}_{|X_t| \leq 1} dt \right] \leq (N+1)(N^3+1) \left(\frac{1 + \exp(-2N^\zeta)}{2} \right)^N,$$

which, for N sufficiently large, is smaller than $\exp(-N^\zeta/2)$. By a union bound and Chebyshev’s inequality, the \mathbb{P} -probability that

$$\exists x \approx 0 : \mathbf{E}_x^{\tau_N} \left[\int_{N^{\zeta-1}}^{N^3+1} \mathbf{1}_{|X_t| \leq 1} dt \right] > \exp(-N^\zeta/4) \tag{10.18}$$

tends to 0 as N tends to infinity. We now argue that the probability appearing on the left-hand side of (10.18) is, up to some power of N , an upper bound for the probability in (10.17). More precisely, let us write

$$H_N = \inf\{t \geq N^{\zeta-1} : |X_t| \leq 1\},$$

and observe that

$$\begin{aligned} \mathbf{E}_x^{\tau_N} \left[\int_{N^{\zeta-1}}^{N^3+1} \mathbf{1}_{|X_t| \leq 1} dt \right] &\geq \mathbf{E}_x^{\tau_N} \left[\mathbf{1}_{H_N \leq N^3} \int_{N^{\zeta-1}}^{N^3+1} \mathbf{1}_{|X_t| \leq 1} dt \right] \\ &\geq \mathbf{E}_x^{\tau_N} \left[\mathbf{1}_{H_N \leq N^3} \int_{H_N}^{H_N+1} \mathbf{1}_{X_t = X_{H_N}} dt \right] \\ &\geq \mathbf{E}_x^{\tau_N} \left[\mathbf{1}_{H_N \leq N^3} \mathbf{E}_{X_{H_N}}^{\tau_N} \left[\int_0^1 \mathbf{1}_{X_t = X_0} dt \right] \right]. \end{aligned} \tag{10.19}$$

where we applied the Markov property at time H_N in the last step. The total time spent on site $y \in V_N$ is an exponential random variable with parameter

$$\tau_{N,y} = e^{a_N E_y} \sum_{z \sim y} e^{a_N E_z}.$$

Note that

$$\mathbb{E} [\tau_{N,y}] = N \phi(a_N)^2 \leq 2N \left(e^{\bar{a} \log N} \right)^2 = 2N^{1+2\bar{a}}.$$

In particular, since we assume $\bar{a} \leq 1$, the \mathbb{P} -probability that

$$\forall y \text{ s.t. } |y| \leq 1, \tau_{N,y} \leq N^5 \tag{10.20}$$

tends to 1 as N tends to infinity. We define Ω'_N as the set where the event displayed in (10.20) and the complement of the event displayed in (10.18) hold. We have seen that $\mathbb{P} [\Omega'_N]$ tends to 1 as N tends to infinity. For $\tau_N \in \Omega'_N$, we have

$$\forall y \text{ s.t. } |y| \leq 1, \mathbf{E}_y^{\tau_N} \left[\int_0^1 \mathbf{1}_{X_t = X_0} dt \right] \geq \frac{1}{2N^5}.$$

In view of (10.19), it thus follows that

$$\mathbf{E}_x^{\tau_N} \left[\int_{N^{\zeta-1}}^{N^{\zeta+1}} \mathbf{1}_{|X_t| \leq 1} dt \right] \geq \frac{\mathbf{P}_x^{\tau_N} [H_N \leq N^3]}{2N^5}.$$

Using also the fact that when $\tau_N \in \Omega'_N$, the complement of the event displayed in (10.18) holds, we obtain that for any $x \approx 0$,

$$\mathbf{P}_x^{\tau_N} [H_N \leq N^3] \leq 2N^5 \exp(-N^\zeta/4),$$

and this finishes the proof. □

Proof of Theorem 10.1 Let us write

$$\ell = \int_0^{\tilde{e}_N(1)} \mathbf{1}_{X_t=0} dt,$$

where we recall that $\tilde{e}_N(1)$ is an exponential random variable of parameter $1/N^2$, independent of everything else. It follows from (9.1) that

$$G_N(\tau_N) = \mathbf{E}_0^{\tau_N} [\ell].$$

Since ℓ is the total time spent at a point by a certain transient Markov chain (the chain X with killing parameter $1/N^2$), we have in fact that under $\mathbf{P}_0^{\tau_N}$, the random variable ℓ follows an exponential distribution with mean $G_N(\tau_N)$.

We decompose $\mathbf{E}_0^{\tau_N} [\ell]$ as

$$\mathbf{E}_0^{\tau_N} \left[\int_0^{H_2} \mathbf{1}_{X_t=0} dt \right] + \mathbf{E}_0^{\tau_N} \left[\int_{H_2}^{\tilde{e}_N(1)} \mathbf{1}_{X_t=0} dt \right]. \tag{10.21}$$

Our first step is to show that the second term in this sum is small. Note that it may be negative, since it may happen that $H_2 > \tilde{e}_N(1)$. We bound its absolute value by

$$\mathbf{E}_0^{\tau_N} [H_2, H_2 > \tilde{e}_N(1)] + \mathbf{E}_0^{\tau_N} \left[\int_{H_2}^{\tilde{e}_N(1)} \mathbf{1}_{X_t=0} dt, H_2 \leq \tilde{e}_N(1) \right]. \tag{10.22}$$

The random variable H_2 can be decomposed as the time spent on the origin before reaching level 2, say $H_2^{(0)}$, plus the time spent at level 1 before reaching level 2, say $H_2^{(1)}$. The random variable $H_2^{(0)}$ follows an exponential distribution whose parameter is displayed in (10.1) (with $x = 0$), and takes the form

$$\frac{AB}{A + B},$$

where

$$A = \sum_{y \sim 0} e^{a_N(E_0 + E_y)} \geq N,$$

and

$$B = \sum_{y \sim 0} \sum_{z \sim y, z \neq 0} e^{a_N(E_y + E_z)} \geq N.$$

As a consequence, we have

$$AB \geq N(A + B)/2,$$

which implies that $H_2^{(0)}$ is dominated by an exponential random variable of parameter $N/2$. As for $H_2^{(1)}$, at any site at distance 1 from the origin, the walk may jump at distance 2 with a transition rate at least $(N - 1)$. Hence, $H_2^{(1)}$ is dominated by an exponential random variable of parameter $(N - 1)$. The first term in (10.22) is smaller than

$$\mathbf{E}_0^{\tau_N} [H_2^2]^{1/2} \mathbf{P}_0^{\tau_N} [H_2 > \tilde{e}_N(1)]^{1/2},$$

and this is exponentially small in N (uniformly over τ_N) by the above observations, since

$$\mathbf{P}_0^{\tau_N} [H_2 > \tilde{e}_N(1)] \leq \mathbf{P}_0^{\tau_N} [H_2 > 1] + \mathbf{P}_0^{\tau_N} [1 \leq \tilde{e}_N(1)].$$

We now turn to the second term appearing in (10.22). Recalling the definition of \mathfrak{A}_N given in (10.5), we define $\tilde{\mathfrak{A}}_N$ as the conjunction of \mathfrak{A}_N , $H_2 \leq \tilde{e}_N(1)$ and $\tilde{e}_N(1) \leq N^3$. By Proposition 10.6 and the above observations, we know that

$$\overline{\mathbb{P}}_N^\circ [\tilde{\mathfrak{A}}_N] \xrightarrow{N \rightarrow \infty} 1.$$

It thus follows from Chebyshev’s inequality that there exists a sequence ε_N tending to 0 and such that

$$\mathbb{P}^\circ \left[\mathbf{P}_0^{\tau_N} [\tilde{\mathfrak{A}}_N^c] > \varepsilon_N \right] \leq \varepsilon_N$$

(indeed, it suffices to take $\varepsilon_N^2 = \overline{\mathbb{P}}_N^\circ [\tilde{\mathfrak{A}}_N]$). From now on, we only consider environments τ_N such that

$$\mathbf{P}_0^{\tau_N} [\tilde{\mathfrak{A}}_N^c] \leq \varepsilon_N. \tag{10.23}$$

We rewrite the second term appearing in (10.22) as

$$\begin{aligned} & \mathbf{E}_0^{\tau_N} \left[\int_{H_2}^{\tilde{e}_N(1)} \mathbf{1}_{X_t=0} dt, H_2 \leq \tilde{e}_N(1) \right] \\ &= \mathbf{E}_0^{\tau_N} \left[\int_{H_2}^{\tilde{e}_N(1)} \mathbf{1}_{X_t=0} dt, \tilde{\mathfrak{A}}_N \right] + \mathbf{E}_0^{\tau_N} \left[\int_{H_2}^{\tilde{e}_N(1)} \mathbf{1}_{X_t=0} dt, H_2 \leq \tilde{e}_N(1), \tilde{\mathfrak{A}}_N^c \right]. \end{aligned} \tag{10.24}$$

The second term in the right-hand side above is bounded by

$$\mathbf{E}_0^{\tau_N} \left[\ell, \tilde{\mathfrak{A}}_N^c \right] \leq \underbrace{\mathbf{E}_0^{\tau_N} \left[\ell^2 \right]}^{1/2} \mathbf{P}_0^{\tau_N} \left[\tilde{\mathfrak{A}}_N^c \right]^{1/2},$$

by the Cauchy–Schwarz inequality. Since ℓ is an exponential random variable of parameter $G_N(\tau_N)$, the quantity underbraced above is equal to $\sqrt{2} G_N(\tau_N)$. Since we also focus on environments such that (10.23) holds, we thus have

$$0 \leq \mathbf{E}_0^{\tau_N} \left[\int_{H_2}^{\tilde{e}_N(1)} \mathbf{1}_{X_t=0} dt, H_2 \leq \tilde{e}_N(1), \tilde{\mathfrak{A}}_N^c \right] \leq \sqrt{2\varepsilon_N} G_N(\tau_N). \tag{10.25}$$

We now consider the first term in the right-hand side of (10.24). By the definition of the event $\tilde{\mathfrak{A}}_N$, this term is (positive and) smaller than

$$\mathbf{E}_0^{\tau_N} \left[\int_{H_2+N^{\zeta-1}}^{N^3} \mathbf{1}_{X_t=0} dt, \tilde{\mathfrak{A}}_N \right].$$

By the Markov property at time H_2 , this is smaller than

$$\mathbf{E}_0^{\tau_N} \left[\mathbf{E}_{X_{H_2}}^{\tau_N} \left[\int_{N^{\zeta-1}}^{N^3} \mathbf{1}_{X_t=0} dt, \overline{\mathfrak{A}}_N \right] \right], \tag{10.26}$$

where we wrote $\overline{\mathfrak{A}}_N$ for the event

$$\inf\{t \geq 0 : |X_t| \leq 1\} \geq N^{\zeta-1}.$$

Since X_{H_2} is at distance 2 from the origin, the quantity in (10.26) is bounded by

$$\sum_{x:|x|=2} \mathbf{E}_x^{\tau_N} \left[\int_{N^{\zeta-1}}^{N^3} \mathbf{1}_{X_t=0} dt, \bar{\mathfrak{A}}_N \right] \leq N^3 \sum_{x:|x|=2} \mathbf{P}_x^{\tau_N} \left[\underbrace{\bar{\mathfrak{A}}_N \text{ and } \exists t \text{ s.t. } N^{\zeta-1} \leq t < N^3, |X_t| \leq 1}_{\text{event}} \right]. \tag{10.27}$$

The crucial point of our argument is that the event underbraced above does not depend on $\tau_{N,0}$. Indeed, it is a function of the trajectory up to hitting the 1-neighbourhood of 0, and this does not depend on $\tau_{N,0}$. Let us write

$$\Omega_N^\circ = \{ \tau_N : \exists \tau'_N \text{ s.t. } \tau_N \text{ and } \tau'_N \text{ are equal outside of 0 and moreover, } \tau'_N \in \Omega'_N \},$$

where Ω'_N is given by Lemma 10.9. The probability $\mathbb{P}^\circ[\Omega_N^\circ]$ tends to 1 as N tends to infinity. For any $\tau_N \in \Omega_N^\circ$, there exists $\tau'_N \in \Omega'_N$ that agrees with τ_N outside of 0. For such τ_N and τ'_N , we have

$$\begin{aligned} & \mathbf{P}_x^{\tau_N} \left[\bar{\mathfrak{A}}_N \text{ and } \exists t \text{ s.t. } N^{\zeta-1} \leq t < N^3, |X_t| \leq 1 \right] \\ &= \mathbf{P}_x^{\tau'_N} \left[\bar{\mathfrak{A}}_N \text{ and } \exists t \text{ s.t. } N^{\zeta-1} \leq t < N^3, |X_t| \leq 1 \right], \end{aligned}$$

and the right-hand side is smaller than $\exp(-N^{\zeta/2})$ for any $x \approx 0$ by Lemma 10.9. As a consequence, the left-hand side of (10.27), and thus also the first term in the right-hand side of (10.24), is smaller than $\exp(-N^{\zeta/4})$ for all N sufficiently large, provided $\tau_N \in \Omega_N^\circ$.

To sum up, we have shown that there exists $\bar{\Omega}_N$ such that $\mathbb{P}^\circ[\bar{\Omega}_N]$ tends to 1 as N tends to infinity, and moreover, for any $\tau_N \in \bar{\Omega}_N$,

$$\left| G_N(\tau_N) - \mathbf{E}_0^{\tau_N} \left[\int_0^{H_2} \mathbf{1}_{X_t=0} dt \right] \right| \leq e^{-cN} + \sqrt{2\varepsilon_N} G_N(\tau_N) + \exp(-N^{\zeta/4}), \tag{10.28}$$

where $c > 0$ and we recall that $\lim \varepsilon_N = 0$. To conclude, it thus suffices to see that for any $\varepsilon > 0$, there exists Ω''_N such that $\mathbb{P}^\circ[\Omega''_N]$ tends to 1 as N tends to infinity, and moreover, for any $\tau_N \in \Omega''_N$,

$$\mathbf{E}_0^{\tau_N} \left[\int_0^{H_2} \mathbf{1}_{X_t=0} dt \right] = (1 \pm \varepsilon) N^{-2} \phi(a_N)^{-2} \tag{10.29}$$

as soon as N is sufficiently large. Indeed, showing (10.29) is sufficient in view of (10.28) since

$$N^{-2}\phi(a_N)^{-2} \geq N^{-2} \left(e^{\bar{a} \log N} \right)^{-2} \geq N^{-4},$$

which is much larger than $\exp(-N^{\zeta/4})$. By Lemma 10.2, the left-hand side of (10.29) is equal to the inverse of the quantity in (10.1) taken for $x = 0$. By Proposition 10.3, there exists Ω''_N such that $\mathbb{P}^\circ[\Omega''_N]$ tends to 1 as N tends to infinity, and moreover, for any $\tau_N \in \Omega''_N$,

$$\tau_{N,0} \geq \delta B_N \quad \text{and} \quad \sum_{x \sim 0} e^{a_N E_x} \sum_{y \sim x, y \neq 0} e^{a_N E_y} = (1 \pm \varepsilon) N^2 \phi(a_N)^2, \quad (10.30)$$

since the second condition does not involve $\tau_{N,0}$. Under the conditions displayed in (10.30), the parameter in (10.1), taken for $x = 0$, is equal to

$$\begin{aligned} & e^{a_N E_0} \sum_{y \sim 0} e^{a_N E_y} \frac{(1 \pm \varepsilon) N^2 \phi(a_N)^2}{e^{a_N E_0} \sum_{y \sim 0} e^{a_N E_y} + (1 \pm \varepsilon) N^2 \phi(a_N)^2} \\ &= (1 \pm \varepsilon) N^2 \phi(a_N)^2 \frac{e^{a_N E_0} \sum_{y \sim 0} e^{a_N E_y}}{e^{a_N E_0} \sum_{y \sim 0} e^{a_N E_y} + (1 \pm \varepsilon) N^2 \phi(a_N)^2}. \end{aligned} \quad (10.31)$$

Recalling that $B_N = \exp(\beta \sqrt{N} b_N)$ and $b_N \sim \sqrt{2cN}$, it comes that if $\tau_{N,0} = \exp(\beta \sqrt{N} E_0) \geq \delta B_N$, then it must be that $E_0 \geq N^{1/4}$. Since $a_N \geq 1$, we also have $\exp(a_N E_0) \geq \exp(N^{1/4})$. Consequently, the fraction appearing in the right-hand side of (10.31) tends to 1 as N tends to infinity, and this completes the proof. \square

11 The Green function at the deep trap

The purpose of this section is to show the following theorem.

Theorem 11.1 *Under the measure $\bar{\mathbb{P}}_N$, the random variable $N^2 \phi(a_N)^2 G_N(\tau_N^{(\delta)}(1))$ converges to 1 in probability.*

What Theorem 9.1 says about $G_N(\tau_N^{(\delta)}(1))$ is that its size-biased distribution is the distribution of $G_N(\tau_N)$ under \mathbb{P}° . In the previous section, we characterized the latter distribution. Knowing the size-bias of a distribution is however not sufficient to characterize it in general. Indeed, consider that any non-identically zero Bernoulli random variable has the constant 1 as its size-biased distribution. As we will now see, in order to conclude, it suffices to show that $G_N(\tau_N^{(\delta)}(1))$ cannot take values smaller than $cN^{-2}\phi(a_N)^{-2}$ for some $c > 0$. This is the content of the next proposition.

Proposition 11.2 *We have*

$$\bar{\mathbb{P}}_N \left[N^2 \phi(a_N)^2 G_N(\tau_N^{(\delta)}(1)) \geq 1/2 \right] \xrightarrow{N \rightarrow \infty} 1.$$

Proof The quantity $G_N(\tau_N^{(\delta)}(1))$ is bounded from below by the inverse of the parameter displayed in (10.1) with x replaced by $x_N^{(\delta)}(1)$. Moreover, since $x_N^{(\delta)}(1)$ is a deep trap, we have $E_{x_N^{(\delta)}(1)} \geq N^{1/4}$. Reasoning as in (10.31) and the few lines below, we see that in order to prove Proposition 11.2, it suffices to show that

$$\bar{\mathbb{P}}_N \left[\sum_{x \sim x_N^{(\delta)}(1)} e^{a_N E_x} \sum_{y \sim x, y \neq x_N^{(\delta)}(1)} e^{a_N E_y} \leq 2N^2 \phi(a_N)^2 \right] \xrightarrow{N \rightarrow \infty} 1. \tag{11.1}$$

We will prove (11.1) with the same technique as the one used to prove Lemma 9.12. Let $\varepsilon \in (0, 1)$, and

$$\mathcal{W}_N = \{x \in V_N : |x| \leq 2\}.$$

We say that a site $z \in V_N$ is *atypical* if both

$$\tau_{N,z} \geq \delta B_N$$

and

$$\sum_{x \sim z} e^{a_N E_x} \sum_{y \sim x, y \neq z} e^{a_N E_y} \neq (1 \pm \varepsilon) N^2 \phi(a_N)^2 \tag{11.2}$$

hold (where we write $\mathbf{a} \neq (1 \pm \varepsilon)\mathbf{b}$ to mean that there exists no \mathbf{c} such that $|\mathbf{c}| \leq \varepsilon$ and $\mathbf{a} = (1 + \mathbf{c})\mathbf{b}$). We say that $z \in V_N$ is *uncommon* if

$$\exists z' : z' \in z + \mathcal{W}_N \text{ and } z' \text{ is atypical.}$$

For $\Gamma \subseteq V_N$, we say that z is *uncommon regardless of Γ* if

$$\exists z' : z' \in z + \mathcal{W}_N, (z' + \mathcal{W}_N) \cap \Gamma = \emptyset \text{ and } z' \text{ is atypical.}$$

In order to show that (11.1) holds, it suffices to show that

$$\bar{\mathbb{P}}_N \left[x_N^{(\delta)}(1) \text{ is atypical} \right] \xrightarrow{N \rightarrow \infty} 0.$$

As in the proof of Lemma 9.12, if $x_N^{(\delta)}(n)$ is atypical, then there must exist $k \leq r_N^{(\delta)}(n)$ such that x_k is uncommon regardless of $\{x_1, \dots, x_{k-1}\}$. We recall that the probability in (9.28) can be made arbitrarily small if C_r is taken large enough. It thus suffices to show that

$$\bar{\mathbb{P}}_N \left[x_N^{(\delta)}(n) \text{ is atypical, } r_N^{(\delta)}(n) \leq C_r \mathbf{d}_N \right]$$

tends to 0 with N . This probability is bounded by

$$\sum_{k=1}^{C_r d_N} \bar{\mathbb{P}}_N [x_k \text{ is uncommon regardless of } \{x_1, \dots, x_{k-1}\}].$$

Every summand is bounded by $\mathbb{P}[0 \text{ is uncommon}]$, which itself is smaller than

$$|\mathcal{W}_N| \mathbb{P}[0 \text{ is atypical}] = |\mathcal{W}_N| \mathbb{P}[\tau_{N,0} \geq \delta B_N] \mathbb{P}[(11.2) \text{ holds with } z = 0]. \tag{11.3}$$

The conclusion follows since $d_N \mathbb{P}[\tau_{N,0} \geq \delta B_N]$ converges to a constant, $|\mathcal{W}_N| = O(N^2)$, while the last probability in (11.3) is $o(N^{-2})$ by Proposition 10.3. \square

Proof of Theorem 11.1 Let A be a measurable subset of $[1/2, +\infty)$, and define

$$h_N(\tau_N) = \frac{1}{2N^2 \phi(a_N)^2 G_N(\tau_N)} \mathbf{1}_{N^2 \phi(a_N)^2 G_N(\tau_N) \in A}.$$

We have $\|h_N\|_\infty \leq 1$. Let $\varepsilon > 0$. We learn from Theorem 9.1 that for any M large enough and any N large enough,

$$\bar{\mathbb{E}}_N \left[(h_N G_N)(\tau_N^{(\delta)}(1)), \mathcal{E}_N^M \right] = \frac{t_N}{d_N} (\mathbb{E}[h_N(\tau) \mid \tau_{N,0} \geq \delta B_N] \pm \varepsilon). \tag{11.4}$$

Moreover, if M is chosen sufficiently large, then for any N large enough, we have

$$\bar{\mathbb{P}}_N \left[\mathcal{E}_N^M \right] \geq 1 - \varepsilon, \tag{11.5}$$

as follows from Propositions 7.1 and 9.11. From now on, we fix M such that this and identity (11.4) hold. Identity (11.4) can be rewritten as

$$\begin{aligned} & \bar{\mathbb{P}}_N \left[N^2 \phi(a_N)^2 G_N(\tau_N^{(\delta)}(1)) \in A, \mathcal{E}_N^M \right] \\ &= N^2 \phi(a_N)^2 \frac{t_N}{d_N} \left(\mathbb{E}^\circ \left[\left(N^2 \phi(a_N)^2 G_N(\tau_N) \right)^{-1} \mathbf{1}_{N^2 \phi(a_N)^2 G_N(\tau_N) \in A} \right] \pm 2\varepsilon \right). \end{aligned} \tag{11.6}$$

We first choose $A = [1/2, +\infty)$. In this case, we know from (11.5) and Proposition 11.2 that the left-hand side is equal to $(1 \pm 2\varepsilon)$ for all large enough N . On the other hand, the expectation on the right-hand side converges to 1 by Theorem 10.1, since the integrand is bounded by 2. We thus get that for any N large enough,

$$N^2 \phi(a_N)^2 \frac{t_N}{d_N} = \frac{1 \pm 2\varepsilon}{1 \pm 3\varepsilon}.$$

Since this holds for arbitrary $\varepsilon > 0$, we have shown that

$$N^2\phi(a_N)^2 \frac{t_N}{d_N} \xrightarrow{N \rightarrow \infty} 1. \tag{11.7}$$

Using this information, we can rewrite (11.6) as

$$\begin{aligned} & \bar{\mathbb{P}}_N \left[N^2\phi(a_N)^2 G_N(\tau_N^{(\delta)}(1)) \in A, \mathcal{E}_N^M \right] \\ &= (1 \pm \varepsilon) \left(\mathbb{E}^\circ \left[\left(N^2\phi(a_N)^2 G_N(\tau_N) \right)^{-1} \mathbf{1}_{N^2\phi(a_N)^2 G_N(\tau_N) \in A} \right] \pm 2\varepsilon \right). \end{aligned}$$

We now choose $A = [1 - \eta, 1 + \eta]$. In this case, the expectation in the right-hand side above still converges to 1 by Theorem 10.1. Hence,

$$\begin{aligned} & \bar{\mathbb{P}}_N \left[N^2\phi(a_N)^2 G_N(\tau_N^{(\delta)}(1)) \in [1 - \eta, 1 + \eta], \mathcal{E}_N^M \right] \\ &= (1 \pm \varepsilon)(1 \pm 3\varepsilon). \end{aligned}$$

Using also (11.5), we thus obtain that for any N large enough,

$$\bar{\mathbb{P}}_N \left[N^2\phi(a_N)^2 G_N(\tau_N^{(\delta)}(1)) \in [1 - \eta, 1 + \eta] \right] = (1 \pm \varepsilon)(1 \pm 3\varepsilon) \pm \varepsilon.$$

Since this holds for arbitrary $\varepsilon > 0$, we have shown that

$$\bar{\mathbb{P}}_N \left[N^2\phi(a_N)^2 G_N(\tau_N^{(\delta)}(1)) \in [1 - \eta, 1 + \eta] \right] \xrightarrow{N \rightarrow \infty} 1.$$

The parameter $\eta > 0$ being arbitrary, this completes the proof of Theorem 11.1. \square

As a by-product, we also proved (11.7), which we restate as a proposition for later usage.

Proposition 11.3 *We have*

$$\frac{d_N}{t_N} \sim N^2\phi(a_N)^2 \quad (N \rightarrow \infty). \tag{11.8}$$

12 Handling several traps

What we have achieved up to now is a thorough understanding of the asymptotic behaviour of certain quantities associated with the first deep trap visited, and most importantly, of the behaviour of the Green function at this location.

The purpose of this section is to show that from this information, we can infer the asymptotic joint behaviour of all the relevant quantities at all the deep traps visited, namely: the time it takes to find them, their depths, the value of the Green function there, and the total time actually spent on the sites. In order to do so, we use again the

times introduced in (9.4) and (9.5), which we can slightly simplify by taking $M = \infty$. In particular, we have $T_N^\infty(1) = T_N^{(\delta)}(1)$. For values of n other than 1, it is not true in general that $T_N^\infty(n) = T_N^{(\delta)}(n)$: the difference is that $T_N^{(\delta)}(2)$ is the time when we discover a second deep trap, while $T_N^\infty(2)$ is the time for the process to discover a first deep trap, then wait $\tilde{\tau}_N(1)$, then wait a strong stationary time, and then come at distance 1 to a deep trap again (possibly *the same* as the first). The interest of these times is that they carry a lot of independence, as given by Proposition 9.4.

We define $x_N^\infty(n)$ as the deep trap discovered at time $T_N^\infty(n)$ (with some tie-breaking rule if multiple deep traps are simultaneously discovered). We write $\tau_N^\infty(n)$ for the environment around site $x_N^\infty(n)$, that is, $\tau_N^\infty(n) = \theta_{x_N^\infty(n)} \tau_N$.

Proposition 12.1 *Under the measure $\bar{\mathbb{P}}_N$ and for every n , $N^2 \phi(a_N)^2 G_N(\tau_N^\infty(n))$ converges to 1 in probability.*

Proof We know from Proposition 9.4 that the random variables $(\tau_N^\infty(n))_{n \in \mathbb{N}}$ are independent and identically distributed under $\mathbf{P}_u^{\tau_N}$. In particular, for every $\varepsilon > 0$ and every n ,

$$\begin{aligned} \mathbf{P}_u^{\tau_N} \left[N^2 \phi(a_N)^2 G_N(\tau_N^\infty(n)) \in [1 - \varepsilon, 1 + \varepsilon] \right] \\ = \mathbf{P}_u^{\tau_N} \left[N^2 \phi(a_N)^2 G_N(\tau_N^\infty(1)) \in [1 - \varepsilon, 1 + \varepsilon] \right]. \end{aligned}$$

Recall that $\tau_N^\infty(1) = \tau_N^{(\delta)}(1)$. Taking \mathbb{E} -expectation above and using Theorem 11.1, we obtain the result. □

Recall that $\mathcal{H}_N^{(\delta)}(n)$ is the event that $x_N^{(\delta)}(n)$ is visited during the time interval $[T_N^{(\delta)}(n), T_N^{(\delta)}(n) + N]$. For a time interval I , we say that x is *seen* during I if there exists $s \in I$ such that $|X_s - x| \leq 1$. This differs slightly from the notion of being discovered during I in that it may happen that a point is seen during I , but had already been discovered at a time prior to I .

For $k \in \mathbb{N}$, let $\mathcal{F}_N^{(\delta)}(k)$ be the event defined as the conjunction of

$$\begin{aligned} \text{for every } n \leq k, \mathcal{H}_N^{(\delta)}(n) \text{ holds, and moreover, during} \\ (T_N^{(\delta)}(n), T_N^{(\delta)}(n) + N^3], \text{ no deep trap is discovered;} \end{aligned} \tag{12.1}$$

$$\begin{aligned} \text{for every } n \leq k, \text{ the site } x_N^{(\delta)}(n) \text{ is not seen} \\ \text{during } [0, T_N^{(\delta)}(k + 1)] \setminus [T_N^{(\delta)}(n), T_N^{(\delta)}(n) + N], \end{aligned} \tag{12.2}$$

Proposition 12.2 (1) *For every k , we have*

$$\bar{\mathbb{P}}_N \left[\mathcal{F}_N^{(\delta)}(k) \right] \xrightarrow[N \rightarrow \infty]{} 1.$$

(2) *For every $k \in \mathbb{N}$, with $\bar{\mathbb{P}}_N$ -probability tending to 1, we have $x_N^\infty(n) = x_N^{(\delta)}(n)$ for every $n \leq k$.*

Proof It was seen in Proposition 9.11 and Lemma 9.8 that the event described in (12.1) has $\overline{\mathbb{P}}_N$ -probability tending to 1. We will show that for every $n \in \mathbb{N}$ and every $M > 0$,

$$\overline{\mathbb{P}}_N [x_N^\infty(n) \text{ is not seen during } [T_N^\infty(n) + N, T_N^\infty(n) + Mt_N]] \xrightarrow{N \rightarrow \infty} 1. \tag{12.3}$$

Let us see why this would imply part (2) of the Proposition, and then part (1) as well. First, outside of an event whose probability can be made as close to 0 as desired, we can always assume that $T_N^{(\delta)}(k + 1) \leq Mt_N$, provided we choose M large enough. Hence, (12.3) implies

$$\overline{\mathbb{P}}_N [x_N^\infty(n) \text{ is not seen during } [T_N^\infty(n) + N, T_N^{(\delta)}(k + 1)]] \xrightarrow{N \rightarrow \infty} 1. \tag{12.4}$$

Note that we always have $x_N^{(\delta)}(1) = x_N^\infty(1)$ and $T_N^\infty(1) = T_N^{(\delta)}(1)$. Next, two things could make $x_N^{(\delta)}(2)$ and $x_N^\infty(2)$ different: (i) that a deep trap is discovered during the time interval $(T_N^\infty(1), \tilde{T}_N^\infty(1)]$ (this would define $x_N^{(\delta)}(2)$, but not $x_N^\infty(2)$); or (ii) that the site $x_N^{(\delta)}(1)$ is seen during the time $(\tilde{T}_N^\infty(1), T_N^{(\delta)}(2)]$ (this would define $x_N^\infty(2)$, but not $x_N^{(\delta)}(2)$). With probability tending to 1, we have

$$N \leq \tilde{T}_N^\infty(1) - T_N^\infty(1) \leq N^3,$$

so the $\overline{\mathbb{P}}_N$ -probability of the events described in (i)–(ii) tend to 0 as N tends to infinity by (12.4) and the fact that the event in (12.1) has $\overline{\mathbb{P}}_N$ -probability tending to 1. The reasoning can be continued to cover any n , and we obtain part (2) of the proposition. Finally, part (2) and (12.4) ensure that indeed, the event in (12.2) has $\overline{\mathbb{P}}_N$ -probability tending to 1 as well, and the proof is complete. \square

There remains to prove (12.3). In order to do so, we will need the following lemma.

Lemma 12.3 *We write $t_+ = \max(t, 0)$. For every $M > 0$ and $x \in V_N$, we have*

$$\begin{aligned} & \mathbf{E}_x^{\tau_N} \left[\int_N^{+\infty} e^{-(t - Mt_N)_+ / N^2} \mathbf{1}_{X_t = x_N^\infty(n)} dt \right] \\ & \geq \mathbf{P}_x^{\tau_N} [\exists s \in [N, Mt_N] : X_s = x_N^\infty(n)] G_N(\tau_N^\infty(n)). \end{aligned} \tag{12.5}$$

Proof of Lemma 12.3 Let

$$\mathcal{T} = \inf\{s \geq N : X_s = x_N^\infty(n)\}.$$

The left-hand side of (12.5) is larger than

$$\begin{aligned} & \mathbf{E}_x^{\tau_N} \left[\mathbf{1}_{\mathcal{T} \leq M t_N} \int_N^{+\infty} e^{-(t-M t_N)_+/N^2} \mathbf{1}_{X_t = x_N^\infty(n)} dt \right] \\ & \geq \mathbf{E}_x^{\tau_N} \left[\mathbf{1}_{\mathcal{T} \leq M t_N} \int_{\mathcal{T}}^{+\infty} e^{-(t-\mathcal{T})/N^2} \mathbf{1}_{X_t = x_N^\infty(n)} dt \right]. \end{aligned}$$

Applying the Markov property at time \mathcal{T} , we obtain the result. □

For $M > 0$, we study the $\mathbf{P}_u^{\tau_N}$ -probability that the site $x_N^\infty(n)$ is visited during the time interval $[T_N^\infty(n) + N, T_N^\infty(n) + M t_N]$. Using the Markov property at time $T_N^\infty(n)$ and the Lemma at $x = X_{T_N^\infty(n)}$, we see that this probability is bounded by the $\mathbf{E}_u^{\tau_N}$ -expectation of

$$\mathbf{E}_{X_{T_N^\infty(n)}}^{\tau_N} \left[\int_N^{+\infty} e^{-(t-M t_N)_+/N^2} \mathbf{1}_{X_t = x_N^\infty(n)} dt \right] G_N(\tau_N^\infty(n))^{-1}. \tag{12.6}$$

By Proposition 3.4, we know that the expectation in (12.6) is bounded by

$$\int_N^{+\infty} e^{-(t-M t_N)_+/N^2} (2^{-N} + e^{-2t}) dt \leq \frac{M t_N + N^2}{2^N} + e^{-2N},$$

and the latter decays exponentially fast since $\log(t_N) \sim \bar{c}N$ with $\bar{c} < \log 2$. Note that the bound thus obtained on the expectation in (12.6) holds uniformly over the environment.

On the other hand, by Proposition 12.1, outside of an event whose $\bar{\mathbb{P}}_N$ -probability tends to 0 with N , we have

$$N^2 \phi(a_N)^2 G_N(\tau_N^\infty(n)) \geq 1/2.$$

Since $N^2 \phi(a_N)^2 \leq 2N^2 a_N^2$ grows sub-exponentially with N (recall (2.5) and (2.2)), we have shown that

$$\bar{\mathbb{P}}_N [x_N^\infty(n) \text{ is visited during } [T_N^\infty(n) + N, T_N^\infty(n) + M t_N]] \xrightarrow{N \rightarrow \infty} 0. \tag{12.7}$$

We now explain how we can infer (12.3) from this. We begin by proceeding as in the proof of Lemma 9.12 to show that

$$\bar{\mathbb{P}}_N \left[\max_{z \approx x_N^\infty(n)} E_z \leq 2\sqrt{\log N} \right] \xrightarrow{N \rightarrow \infty} 1.$$

Since on the other hand, $E_{x_N^\infty(n)} \geq b_n \sim \sqrt{2cN}$, any visit to a neighbour of $x_N^\infty(n)$ is followed (with probability close to 1) by a visit to $x_N^\infty(n)$ itself shortly afterwards (by a reasoning identical to the proof of Proposition 9.11), so that the probability in (12.3) cannot be large if the one in (12.7) is close to 0.

Proposition 12.4 *Under the measure \mathbb{P}_N and for every n , $N^2\phi(a_N)^2 G_N(\tau_N^{(\delta)}(n))$ converges to 1 in probability.*

Proof This is a direct consequence of Proposition 12.1 and part (2) of Proposition 12.2. □

Recall that we write $H_N^{(\delta)}(n)$ for the first time the site $x_N^{(\delta)}(n)$ is visited, and that we defined $e_N^{(\delta)}(n)$ by the relation

$$H_N^{(\delta)}(n) + \tilde{e}_N(n) \int_{H_N^{(\delta)}(n)} \mathbf{1}_{X_t = x_N^{(\delta)}(n)} dt = G_N(\tau_N^{(\delta)}(n)) e_N^{(\delta)}(n).$$

Proposition 12.5 *Under \mathbb{P}_N , the family of triples*

$$((\mathbf{t}_N^{-1}(T_N^{(\delta)}(n) - T_N^{(\delta)}(n - 1)), B_N^{-1} \tau_{N, x_N^{(\delta)}(n)}, e_N^{(\delta)}(n)))_{n \in \mathbb{N}}$$

jointly converges in distribution as N tends to infinity (where we let $T_N^{(\delta)}(0) = 0$). Let us write

$$((T^{(\delta)}(n) - T^{(\delta)}(n - 1), \tau^{(\delta)}(n), e^{(\delta)}(n))_{n \in \mathbb{N}} \tag{12.8}$$

for limiting random variables, which we assume to be defined on the \mathbb{P} -probability space for convenience (these can be taken as an extension of those appearing in Proposition 7.1, and we fix $T_N^{(\delta)}(0) = 0$). Their joint distribution is described as follows. The family of triples in (12.8) is a family of i.i.d. triples. Moreover, the random variables $T^{(\delta)}(1)$, $\tau^{(\delta)}(1)$ and $e^{(\delta)}(1)$ are themselves independent. Their respective distributions are exponential of parameter $\delta^{-\alpha}$, the law displayed in (7.1), and exponential of parameter 1.

Proof We introduce a slight modification of the sequence of times $(T_N^\infty(n))_{n \in \mathbb{N}}$, that we write $(T'_N(n))_{n \in \mathbb{N}}$. They are constructed in the same way as the sequence $(T_N^\infty(n))_{n \in \mathbb{N}}$, except for the fact that $T'_N(1)$ is the first time when a deep trap is visited by the walk (instead of being simply discovered). More precisely, we let $\tilde{T}'_N(0) = 0$,

$$T'_N(1) = \inf\{t : \tau_{N, X_t} \geq \delta B_N\},$$

and then define recursively, for any $n \in \mathbb{N}$,

$$\begin{aligned} T'_N(n) &= \tilde{T}'_N(n - 1) + T'_N(1) \circ \Theta_{\tilde{T}'_N(n-1)}, \\ \tilde{T}'_N(n) &= T'_N(n) + \tilde{e}_N(n) + \mathbf{T}_N \circ \Theta_{T'_N(n) + \tilde{e}_N(n)}. \end{aligned}$$

We let $x'_N(n)$ be the deep trap visited at time $T'_N(n)$, $\tau'_N(n) = \theta_{x'_N(n)} \tau_N$, and $e'_N(n)$ be such that

$$\int_{T'_N(n)}^{T'_N(n)+\tilde{e}_N(n)} \mathbf{1}_{X_t=x'_N(n)} dt = e'_N(n) G_N(\tau'_N(n)).$$

As follows from Proposition 9.4, the family of triples

$$((T'_N(n) - \tilde{T}'_N(n - 1), \tau_{N,x'_N(n)}, e'_N(n)))_{n \in \mathbb{N}}$$

is a family of i.i.d. triples under $\mathbf{P}_u^{\tau_N}$. Moreover, the pair $(T'_N(n) - \tilde{T}'_N(n - 1), \tau_{N,x'_N(n)})$ is independent of $e'_N(n)$ under $\mathbf{P}_u^{\tau_N}$. Indeed, conditionally on the history of the walk up to time $T'_N(n)$, the random variable $e'_N(n)$ is simply an exponential random variable of parameter 1 (the argument is the same as the one in the paragraph below (9.27)). Note that from this argument, we also learn what is the distribution of $e'_N(n)$.

For definiteness, let us look at the Fourier transform of the random variables under consideration. By the above remarks, for every τ_N , every $k \in \mathbb{N}$ and every $x_n, y_n, z_n \in \mathbb{R}$, we have

$$\begin{aligned} & \mathbf{E}_u^{\tau_N} \left[\exp \left(\sum_{n=1}^k i x_n t_N^{-1} (T'_N(n) - \tilde{T}'_N(n - 1)) + i y_n B_N^{-1} \tau_{N,x'_N(n)} + i z_n e'_N(n) \right) \right] \\ &= \mathbf{E}_u^{\tau_N} \left[\exp \left(\sum_{n=1}^k i x_n t_N^{-1} (T'_N(n) - \tilde{T}'_N(n - 1)) + i y_n B_N^{-1} \tau_{N,x'_N(n)} \right) \right] \prod_{n=1}^k \frac{1}{1 - i z_n}. \end{aligned} \tag{12.9}$$

We now argue that as N tends to infinity, the difference between

$$\overline{\mathbb{E}}_N \left[\exp \left(\sum_{n=1}^k i x_n t_N^{-1} (T'_N(n) - \tilde{T}'_N(n - 1)) + i y_n B_N^{-1} \tau_{N,x'_N(n)} + i z_n e'_N(n) \right) \right] \tag{12.10}$$

and

$$\overline{\mathbb{E}}_N \left[\exp \left(\sum_{n=1}^k i x_n t_N^{-1} (T_N^{(\delta)}(n) - T_N^{(\delta)}(n - 1)) + i y_n B_N^{-1} \tau_{N,x_N^{(\delta)}(n)} + i z_n e_N^{(\delta)}(n) \right) \right] \tag{12.11}$$

tends to 0 as N tends to infinity. First, we have already seen several times that the difference between $\tilde{T}'_N(n - 1)$ and $T'_N(n - 1)$ is subexponential (to be precise, it is smaller than N^3 with probability tending to 1). So in (12.10), if we replace $\tilde{T}'_N(n - 1)$ by $T'_N(n - 1)$, then the error made tends to 0 as N tends to infinity.

The first deep trap discovered is $x_N^{(\delta)}(1)$ and at time $T_N^{(\delta)}(1)$. On the event $\mathcal{F}_N(k)$, we know that $x_N^{(\delta)}(1)$ is actually visited during the time interval $[T_N^{(\delta)}(1), T_N^{(\delta)}(1) + N]$, and that no other deep trap is discovered during this time interval, so $x_N^{(\delta)}(1) = x'_N(1)$. On this event, the definitions of $e'_N(1)$ and $e_N^{(\delta)}(1)$ actually coincide. Note also that on this event, we have $T_N^{(\delta)}(1) \leq T'_N(1) \leq T_N^{(\delta)}(1) + N$. Proceeding as in the proof of part (2) of Proposition 12.2, we can iterate this reasoning to subsequent sites, and obtain that indeed the difference between (12.10) and (12.11) converges to 0 as N tends to infinity.

In order to conclude, we want to take the \mathbb{E} -expectation in (12.9) and identify the right-hand side as the “correct answer”. Note that the limit of

$$\mathbb{E}_N \left[\exp \left(\sum_{n=1}^k i x_n t_N^{-1} (T_N^{(\delta)}(n) - T_N^{(\delta)}(n - 1)) + i y_n B_N^{-1} \tau_{N, x_N^{(\delta)}(n)} \right) \right]$$

as N tends to infinity is known and given by Proposition 7.1. By the fact that we can replace $x_N^{(\delta)}(n)$ by $x'_N(n)$ above, we obtain explicitly the limit of the \mathbb{E} -expectation of the right-hand side of (12.9), and this is also the limit of

$$\mathbb{E}_N \left[\exp \left(\sum_{n=1}^k i x_n t_N^{-1} (T_N^{(\delta)}(n) - T_N^{(\delta)}(n - 1)) + i y_n B_N^{-1} \tau_{N, x_N^{(\delta)}(n)} + i z_n e_N^{(\delta)}(n) \right) \right],$$

so the proof is complete. □

13 Convergence of the clock process

In this section, we obtain the scaling limit of the clock process.

Theorem 13.1 *Recall that we assume (2.2) with $\bar{a} < 1/20$, that (t_N) satisfies $\log t_N \sim \bar{c}N$ with $\bar{c} \in (0, \log(2))$, that d_N is given by Theorem 5.1 (and satisfies (11.8)), that ϕ , B_N and α are defined in (2.5), (6.3) and (6.5) respectively, and that we assume $\alpha < 1$. Let*

$$C(t) = \int_0^t \tau_{N, X_s} \, ds \tag{13.1}$$

be the clock process, and let C_N be its rescaled version, defined by

$$C_N(t) = N^2 \phi(a_N)^2 B_N^{-1} C(t t_N). \tag{13.2}$$

Under \mathbb{P}_N , the rescaled clock process C_N converges in distribution, for the M_1 topology and as N tends to infinity, to the α -stable subordinator \mathcal{C} whose Lévy measure is given by

$$\Gamma(\alpha + 1) \frac{\alpha \, dz}{z^{\alpha+1}},$$

where Γ is Euler’s Gamma function.

Remark 13.2 The M_1 topology is defined on the space of càd-làg functions, we refer to [41, (3.3.4)] for a precise definition. Here, we understand the convergence of processes defined on \mathbb{R}_+ as the convergence of the restriction of the processes on $[0, t]$ for every $t > 0$.

Remark 13.3 In Theorem 13.1, as in the next Theorem 14.1 on the convergence of the age process, we impose two restrictions on the time scale, namely $\bar{c} \in (0, \log(2))$ and $\bar{c} < \beta^2/2$, this last inequality being equivalent to the condition $\alpha < 1$.

We note that we thus cover all possible time scales. Indeed, the convergence of the clock process towards a subordinator can only hold on time scales that are shorter than the equilibrium time. Let us see that this corresponds to the restriction $\bar{c} < \log(2) \wedge \beta^2/2$.

Remember that we are considering a time t_N such that $\log(t_N) \sim \bar{c}N$. This corresponds to looking at the process Z up to times of order B_N (on the exponential scale), with $\log(B_N) \sim \beta\sqrt{2\bar{c}}N$.

On the one hand, by general facts on reversible Markov chains, we know that the process Z has reached equilibrium for times larger than the inverse spectral gap. As can be seen by adapting the arguments in [24], the inverse spectral gap of the dynamics we are considering here is of order $\exp(\beta\beta_c N)$, where $\beta_c = \sqrt{2 \log(2)}$. Imposing that B_N is smaller than $\exp(\beta\beta_c N)$ on the exponential scale leads to the condition $\bar{c} < \log(2)$.

It turns out that the time needed for the dynamics to reach equilibrium when started with the uniform law (as here) may be much shorter than the inverse spectral gap in the high-temperature regime, and should then rather be estimated using generalized Poincaré inequalities. Results in [35] show that if $\beta > \beta_c$, then Z is indeed close to equilibrium by a time of order $\exp(\beta^2 N)$. (The dynamics considered in [35] is rather the RHT dynamics, but the argument readily generalizes to the dynamics considered here as soon as we assume $a_N = o(\sqrt{N})$, and in particular under our present assumption (2.2).) Requiring that, on the exponential scale, B_N is smaller than $\exp \beta^2 N$ is equivalent to assuming that $\bar{c} < \beta^2/2$.

Let

$$C_N^{(\delta)}(t) = N^2 \phi(a_N)^2 B_N^{-1} \int_0^{t t_N} \tau_{N, X_s} \mathbf{1}_{\tau_{N, X_s} \geq \delta B_N} \, ds.$$

$$C_N^{(\delta)}(t) = N^2 \phi(a_N)^2 B_N^{-1} \sum_{n=1}^{+\infty} \tau_{N, X_N^{(\delta)}(n)} e_N^{(\delta)}(n) G_N(\tau_N^{(\delta)}(n)) \mathbf{1}_{t \geq t_N^{-1} T_N^{(\delta)}(n)}.$$

Proposition 13.4 For every $T > 0$, the M_1 distance on between the processes $C_N^{(\delta)}$ and $C_N^{(\delta)}$ restricted to $[0, T]$ converges to 0 in \mathbb{P}_N -probability.

Proof The proof is similar to that of [37, Proposition 6.3]. Let \tilde{B}_N^{-1} be such that

$$\tilde{B}_N^{-1} = N^2 \phi(a_N)^2 B_N^{-1}. \tag{13.3}$$

Let $T > 0$. We begin by showing that for every $n \leq k$, the M_1 distance between

$$\tilde{B}_N^{-1} \int_0^{t_N \wedge T_N^{(\delta)}(k+1)} \tau_{N, X_s} \mathbf{1}_{X_s = x_N^{(\delta)}(n)} \, ds \tag{13.4}$$

and

$$\tilde{B}_N^{-1} \tau_{N, x_N^{(\delta)}(n)} e_N^{(\delta)}(n) G_N(\tau_N^{(\delta)}(n)) \mathbf{1}_{t \geq \mathfrak{t}_N^{-1} T_N^{(\delta)}(n)}, \tag{13.5}$$

as processes defined on $[0, T]$, tends to 0 in $\bar{\mathbb{P}}_N$ -probability. These two processes are increasing. The second process is equal to 0 until time $\mathfrak{t}_N^{-1} T_N^{(\delta)}(n)$, when it jumps to the value

$$\tilde{B}_N^{-1} \tau_{N, x_N^{(\delta)}(n)} e_N^{(\delta)}(n) G_N(\tau_N^{(\delta)}(n)) = \tilde{B}_N^{-1} \tau_{N, x_N^{(\delta)}(n)} \int_{H_N^{(\delta)}(n)}^{H_N^{(\delta)}(n) + \tilde{e}_N(n)} \mathbf{1}_{X_s = x_N^{(\delta)}(n)} \, ds$$

(recall that $H_N^{(\delta)}(n)$ is the first time the walk visits $x_N^{(\delta)}(n)$). We know from Proposition 12.2 that with probability close to 1, the site $x_N^{(\delta)}(n)$ is not visited by the walk during the time interval $[0, T_N^{(\delta)}(k+1)] \setminus [T_N^{(\delta)}(n), T_N^{(\delta)}(n) + N]$. We know also from Proposition 9.11 that with probability tending to 1, $x_N^{(\delta)}(n)$ is indeed visited by the walk during the time interval $[T_N^{(\delta)}(n), T_N^{(\delta)}(n) + N]$. As a consequence, with probability tending to 1, the process in (13.4) is 0 until time $\mathfrak{t}_N^{-1} T_N^{(\delta)}(n)$, and then is constant equal to

$$\begin{aligned} & \tilde{B}_N^{-1} \tau_{N, x_N^{(\delta)}(n)} \int_{T_N^{(\delta)}(n)}^{T_N^{(\delta)}(n) + N} \mathbf{1}_{X_s = x_N^{(\delta)}(n)} \, ds \\ &= \tilde{B}_N^{-1} \tau_{N, x_N^{(\delta)}(n)} \int_{H_N^{(\delta)}(n)}^{H_N^{(\delta)}(n) + \tilde{e}_N(n)} \mathbf{1}_{X_s = x_N^{(\delta)}(n)} \, ds \end{aligned}$$

for all times greater than $\mathfrak{t}_N^{-1} (T_N^{(\delta)}(n) + N)$.

In words, we have argued that the two increasing processes in (13.4) and (13.5) are with high probability equal at every time, except possibly during a time interval whose

length $t_N^{-1}N$ tends to 0 as N tends to infinity. Moreover, by Proposition 12.5, their final value is bounded in probability. These observations ensure that we can construct a parametrization of the completed graphs of these processes, as defined in [41, (3.3.3)], showing that the M_1 distance between the two processes tends to 0, provided we can guarantee that the interval where the two processes possibly differ is far from the endpoints of the interval $[0, T]$. But this is so with high probability, since we know that the limiting distribution of $t_N^{-1} T_N^{(\delta)}(n)$ has a density, see Proposition 12.5.

From this observation, we obtain that the M_1 distance between

$$\sum_{n=1}^k \tilde{B}_N^{-1} \int_0^{t_N \wedge T_N^{(\delta)}(k+1)} \tau_{N, X_s} \mathbf{1}_{X_s = x_N^{(\delta)}(n)} \, ds$$

and

$$\tilde{B}_N^{-1} \sum_{n=1}^k \tau_{N, x_N^{(\delta)}(n)} e^{(\delta)}(n) G_N(\tau_N^{(\delta)}(n)) \mathbf{1}_{t \geq t_N^{-1} T_N^{(\delta)}(n)} \tag{13.6}$$

(as processes defined on $[0, T]$) converges to 0 in $\bar{\mathbb{P}}_N$ -probability. Proposition 12.2 ensures that with probability tending to 1, no other deep trap than $(x_N^{(\delta)}(n))_{n \leq k}$ is visited up to time $T_N^{(\delta)}(k + 1)$. Hence, we obtain that the M_1 distance between

$$\tilde{B}_N^{-1} \int_0^{t_N \wedge T_N^{(\delta)}(k+1)} \tau_{N, X_s} \mathbf{1}_{\tau_{N, X_s} \geq \delta B_N} \, ds$$

and (13.6) converges to 0 as well. Now, in view of Proposition 12.5, this is sufficient, since by choosing k very large, we can make the probability that $t_N^{-1} T_N^{(\delta)}(k + 1) \leq T$ as close to 0 as we wish. \square

Proposition 13.5 *Under $\bar{\mathbb{P}}_N$, the process $C_N^{(\delta)}$ converges in distribution, for the M_1 topology and as N tends to infinity, to the process $C^{(\delta)}$ defined by*

$$C^{(\delta)}(t) = \sum_{n=1}^{+\infty} \tau^{(\delta)}(n) e^{(\delta)}(n) \mathbf{1}_{t \geq T^{(\delta)}(n)},$$

where the random variables

$$(T^{(\delta)}(n), \tau^{(\delta)}(n), e^{(\delta)}(n))_{n \in \mathbb{N}}$$

are distributed as in Proposition 12.5.

Proof By Proposition 13.4, it suffices to study the convergence of $C_N^{(\delta)}$. The proof is then identical to the proof of [37, Proposition 7.5], so we only briefly mention the argument. We use Skorokhod’s representation theorem, so that we can assume that the convergence described in Proposition 12.5 is actually an almost sure convergence. With this in hand, the convergence of the (Skorokhod representation of the) process $C_N^{(\delta)}$ to the (Skorokhod representation of the) process $C^{(\delta)}$ for the M_1 topology easily follows. \square

Proof of Theorem 13.1 Let $T > 0$. We begin by showing that

$$\limsup_{N \rightarrow +\infty} \mathbb{E} \left[\sup_{[0, T]} |C_N^{(\delta)} - C_N| \right] = O(\delta^{1-\alpha}) \quad (\delta \rightarrow 0). \tag{13.7}$$

The process $C_N^{(\delta)} - C_N$ is increasing, and thus

$$\mathbb{E} \left[\sup_{[0, T]} |C_N^{(\delta)} - C_N| \right] = \tilde{B}_N^{-1} \bar{\mathbb{E}}_N \left[\int_0^{Tt_N} \tau_{N, X_s} \mathbf{1}_{\tau_{N, X_s} \leq \delta B_N} ds \right], \tag{13.8}$$

where we recall that \tilde{B}_N was defined in (13.3). Note that the integrand above is simply a function of the environment viewed by the particle, which is stationary under $\bar{\mathbb{P}}_N$. The right-hand side of (13.8) is thus equal to

$$\tilde{B}_N^{-1} T t_N \mathbb{E} \left[\tau_{N, 0} \mathbf{1}_{\tau_{N, 0} \geq \delta B_N} \right].$$

Finally, note that by Proposition 11.3, we have

$$\tilde{B}_N^{-1} t_N \sim B_N^{-1} d_N.$$

Identity (13.7) then follows from (6.6).

We want to complete the following diagram

$$\begin{array}{ccc} C_N^{(\delta)} & \xrightarrow{N \rightarrow \infty} & C^{(\delta)} \\ \downarrow & & \downarrow \quad (\delta \rightarrow 0) \\ C_N & \xrightarrow{N \rightarrow \infty} & C, \end{array}$$

where each arrow represents convergence in distribution for the M_1 topology. Since the uniform norm controls the M_1 distance, we have proved with (13.7) that the convergence of $C_N^{(\delta)}$ to C_N holds uniformly in δ . Proposition 13.5 ensures that $C_N^{(\delta)}$ converges indeed to $C^{(\delta)}$. In order to deduce the convergence of C_N to C (and thus prove Theorem 13.1), what remains to be done (see [14, Theorem 4.2]) is thus simply to show that $C^{(\delta)} \xrightarrow{\delta \rightarrow 0} C$.

Let us thus proceed to prove this convergence. It is clear from its definition that $\mathcal{C}^{(\delta)}$ is a subordinator. Let $\psi_\delta(\lambda)$ be the Laplace exponent of $\mathcal{C}^{(\delta)}$, defined by

$$\mathbb{E}[e^{-\lambda \mathcal{C}^{(\delta)}(t)}] = e^{-t\psi_\delta(\lambda)}.$$

Using the definition of $\mathcal{C}^{(\delta)}(t)$, we obtain that

$$\mathbb{E}[e^{-\lambda \mathcal{C}^{(\delta)}(t)}] = 1 - \frac{t}{\delta^\alpha} + \frac{t}{\delta^\alpha} \mathbb{E}[e^{-\lambda e^{(\delta)}(1)\tau^{(\delta)}(1)}] + O(t^2),$$

and thus

$$\psi_\delta(\lambda) = \frac{1}{\delta^\alpha} \mathbb{E}\left[1 - e^{-\lambda e^{(\delta)}(1)\tau^{(\delta)}(1)}\right].$$

Given the definition of $(e^{(\delta)}(1), \tau^{(\delta)}(1))$ (see Proposition 12.5), we can compute this last quantity. It is equal to

$$\frac{1}{\delta^\alpha} \int_{\substack{y \geq 0 \\ z \geq \delta}} (1 - e^{-\lambda yz}) e^{-y} \frac{\alpha \delta^\alpha}{z^{\alpha+1}} dy dz.$$

The δ^α cancel out. We make the change of variables $u = yz$ to obtain

$$\int_{u=0}^{+\infty} (1 - e^{-u}) \frac{\alpha}{u^{\alpha+1}} \underbrace{\int_{y=0}^{u/\delta} y^\alpha e^{-y} dy}_{\xrightarrow{\delta \rightarrow 0} \Gamma(\alpha+1)} du.$$

By the monotone convergence theorem, we thus obtain that $\psi_\delta(\lambda)$ converges to

$$\Gamma(\alpha + 1) \int_{u=0}^{+\infty} (1 - e^{-u}) \frac{\alpha}{u^{\alpha+1}} du,$$

and this is indeed the Laplace exponent of \mathcal{C} . We have thus shown that for every $t \geq 0$, the Laplace transform of $\mathcal{C}^{(\delta)}(t)$ converges to the Laplace transform of $\mathcal{C}(t)$. Since both processes are subordinators, this ensures convergence in the sense of finite-dimensional distributions. Finally, for increasing processes, convergence of finite-dimensional distributions imply convergence for the M_1 topology (this can be seen directly from the definition, or using the tightness criterion for increasing processes given in [37, Lemma 8.4]; in our case, we could also easily show that the difference between \mathcal{C} and $\mathcal{C}^{(\delta)}$ converges to 0 in probability for the supremum norm). This finishes the proof. □

14 Convergence of the age process

We now discuss the convergence of the age process. In the next theorem as in the next proofs, we use the following definitions. Let f be a càd-làg function. Its inverse is defined as

$$f^{-1}(t) = \inf\{y : f(y) > t\}.$$

Let f be a continuous non-decreasing function. Then $f'(t)$ denotes the right derivative of f at point t (provided it exists).

Theorem 14.1 *Recall the definitions and assumptions summarized in Theorem 13.1. Let*

$$A(t) = \tau_{N, Z_t} \tag{14.1}$$

be the age process, and let A_N be its rescaled version, defined by

$$A_N(t) = B_N^{-1} A\left(t \frac{B_N}{N^2 \phi(a_N)^2}\right). \tag{14.2}$$

Under $\bar{\mathbb{P}}_N$, the rescaled age process A_N converges in distribution, for the $L_{1,loc}$ topology and as N tends to infinity.

The limiting process, say \mathcal{Z} , may be constructed as follows: let Υ be an α -stable subordinator, and let

$$\mathcal{V}_t = \int_0^t T_s \, d\Upsilon_s,$$

where $(T_t)_{t \geq 0}$ is an independent family of independent, mean 1, exponential random variables. Let $\mathcal{W} = \mathcal{V}^{-1}$ be the inverse of \mathcal{V} . Finally, define the process

$$\mathcal{Z}_t = \Upsilon_{\mathcal{W}_t} - \Upsilon_{\mathcal{W}_t-}.$$

In the sequel, we use the notation $\mu(x) = \Upsilon(x) - \Upsilon(x-)$. Note that \mathcal{Z} is a self-similar process of index 1. One checks that its law does not depend on the choice of the α -stable subordinator Υ .

The following proof follows a similar strategy as in [28]. Recall that the processes X and Z are connected through

$$Z_t = X_{C^{-1}(t)},$$

where C is the clock process

$$C(t) = \int_0^t \tau_{N, X_s} \, ds.$$

Observe that

$$A(t) = C' \circ C^{-1}(t).$$

As in the proof of Theorem 13.1, we consider the rescaled version of the clock process

$$C_N(t) = \tilde{B}_N^{-1} \int_0^{t t_N} \tau_{N, X_s} ds$$

(Recall that \tilde{B}_N was defined in (13.3)). Note that

$$C^{-1}(\tilde{B}_N t) = t_N C_N^{-1}(t),$$

and thus

$$A_N(t) = N^{-2} \phi(a_N)^{-2} t_N^{-1} C'_N \circ C_N^{-1}(t) = B_N^{-1} \tau_{N, X(t_N C_N^{-1}(t))}.$$

Also, as in the proof of Theorem 13.1, we introduce truncated processes :

$$C_N^{(\delta)}(t) = \tilde{B}_N^{-1} \int_0^{t t_N} \tau_{N, X_s} \mathbf{1}_{\tau_{N, X_s} \geq \delta B_N} ds$$

and

$$\begin{aligned} A_N^{(\delta)}(t) &= N^{-2} \phi(a_N)^{-2} t_N^{-1} (C_N^{(\delta)})' \circ (C_N^{(\delta)})^{-1}(t); \\ C_N^{(\delta)}(t) &= \tilde{B}_N^{-1} \sum_{n=1}^{+\infty} \tau_{N, x_N^{(\delta)}(n)} e_N^{(\delta)}(n) G_N(\tau_N^{(\delta)}(n)) \mathbf{1}_{t \geq t_N^{-1} T_N^{(\delta)}(n)} \end{aligned}$$

and

$$\mathcal{A}_N^{(\delta)}(t) = B_N^{-1} \tau_{N, x_N^{(\delta)}(n)} \quad \text{for } t \text{ such that } (C_N^{(\delta)})^{-1}(t) = t_N^{-1} T_N^{(\delta)}(n).$$

The proof of the next proposition is similar to the proof of Proposition 13.4.

Proposition 14.2 *For every $T > 0$, the M_1 distance between the processes $A_N^{(\delta)}$ and $\mathcal{A}_N^{(\delta)}$ restricted to $[0, T]$ converges to 0 in $\bar{\mathbb{P}}_N$ -probability.*

Proof Let $k \geq 1$. Observe that on the event $\mathcal{F}_N^{(\delta)}(k)$, the two processes $A_N^{(\delta)}$ and $\mathcal{A}_N^{(\delta)}$ take the same values (namely the sequence $B_N^{-1} \tau_{N, x_N^{(\delta)}(n)}$, for $n \in \{1, \dots, k\}$) in the same order. The holding time at a trap $x_N^{(\delta)}(n)$ is then $C_N^{(\delta)}(t_N^{-1} H_N^{(\delta)}(n + 1)) -$

$C_N^{(\delta)}(\mathfrak{t}_N^{-1}H_N^{(\delta)}(n))$ for the process $A_N^{(\delta)}$, and $C_N^{(\delta)}(\mathfrak{t}_N^{-1}T_N^{(\delta)}(n+1)-) - C_N^{(\delta)}(T_N^{(\delta)}(n)-) = \tilde{B}_N^{-1}e_N^{(\delta)}(n)G_N(\tau_N^{(\delta)}(n))\tau_{N,x_N^{(\delta)}(n)}$ for the process $\mathcal{A}_N^{(\delta)}$. On $\mathcal{F}_N^{(\delta)}(k)$, these two quantities coincide. Therefore the two processes $A_N^{(\delta)}$ and $\mathcal{A}_N^{(\delta)}$ coincide on $\mathcal{F}_N^{(\delta)}(k)$ until time $C_N^{(\delta)}(\mathfrak{t}_N^{-1}H_N^{(\delta)}(k+1))$.

Proposition 12.2 implies that the $\bar{\mathbb{P}}_N$ -probability of $\mathcal{F}_N^{(\delta)}(k)$ tends to 1. Therefore we also have that the M_1 distance between the processes $(A_N^{(\delta)}(t))_{t \leq C_N^{(\delta)}(\mathfrak{t}_N^{-1}H_N^{(\delta)}(k+1))}$ and $(\mathcal{A}_N^{(\delta)}(t))_{t \leq C_N^{(\delta)}(\mathfrak{t}_N^{-1}H_N^{(\delta)}(k+1))}$ tends to 0.

Finally we argue that, by choosing k large, we can make the probability that $C_N^{(\delta)}(\mathfrak{t}_N^{-1}H_N^{(\delta)}(k+1)) \leq T$ as small as we want. On the one hand, the process $C_N^{(\delta)}$ has a limit in distribution, $\mathcal{C}^{(\delta)}$, which is described in Proposition 13.5 and satisfies $\lim_{t \rightarrow +\infty} \mathcal{C}^{(\delta)}(t) = +\infty$. On the other hand, we observe that $\mathfrak{t}_N^{-1}H_N^{(\delta)}(k+1)$ is larger than $\mathfrak{t}_N^{-1}T_N^{(\delta)}(k+1)$ and that the limit in distribution of $\mathfrak{t}_N^{-1}T_N^{(\delta)}(k+1)$, which we wrote $T^{(\delta)}(k+1)$, was obtained in Proposition 12.5 and satisfies $\lim_{k \rightarrow +\infty} T^{(\delta)}(k+1) = +\infty$. □

Next, we introduce truncated versions of the process \mathcal{Z} : enumerate the set $\{x \geq 0 : \mu(x) > \delta\}$ as

$$\{x \geq 0 : \mu(x) > \delta\} = \{v_1 < v_2 < \dots\},$$

and let

$$\mathcal{V}_s^{(\delta)} = \sum_{i=1,2,\dots; v_i \leq s} \mu(v_i) T_{v_i}, \quad s \geq 0,$$

where an empty sum equals 0. We consider the inverse of $\mathcal{V}^{(\delta)}$, say $\mathcal{W}^{(\delta)}$, and let

$$\mathcal{Z}_t^{(\delta)} = \mu(\mathcal{W}_t^{(\delta)}), \quad t \geq 0.$$

Remark 14.3 The trajectories of the process $\mathcal{Z}^{(\delta)}$ are easy to describe: $\mathcal{Z}^{(\delta)}$ successively takes the values $\mu(v_1), \mu(v_2), \dots$ with respective holding times $\mu(v_1)T_{v_1}, \mu(v_2)T_{v_2}, \dots$

Proposition 14.4 *Under $\bar{\mathbb{P}}_N$, the process $A_N^{(\delta)}$ converges in distribution, for the M_1 topology and as N tends to infinity, to the process $\mathcal{Z}^{(\delta)}$.*

Proof By Proposition 14.2, it suffices to study the convergence of $\mathcal{A}_N^{(\delta)}$. We use Skorokhod’s representation theorem, so that we can assume that the convergence described in Proposition 12.5 is actually an almost sure convergence. With this in hand, the convergence of the (Skorokhod representation of the) process $\mathcal{A}_N^{(\delta)}$ to the (Skorokhod representation of the) process $\mathcal{Z}^{(\delta)}$ for the M_1 topology easily follows: compare the description of the process $\mathcal{A}_N^{(\delta)}$ in the proof of Proposition 14.2 with the description of $\mathcal{Z}^{(\delta)}$ in Remark 14.3. □

Proof of Theorem 14.1 Recall that the space of trajectories is equipped with the $L_{1,loc}$ topology. Note that the M_1 is stronger so that Proposition 14.4 also holds for the $L_{1,loc}$ topology.

Let $T > 0$. Let us first show that, for any $\eta > 0$,

$$\limsup_{N \rightarrow +\infty} \mathbb{P} \left[\int_0^T |A_N^{(\delta)}(t) - A_N(t)| dt \geq \eta \right] \xrightarrow{\delta \rightarrow 0} 0. \tag{14.3}$$

It will be convenient to consider the following process: let $\bar{A}_N^{(\delta)}(t)$ be given by $B_N^{-1} \tau_{N,x}$, where x is the last deep trap visited by the process $X(t_N C_N^{-1}(\cdot))$ before time t , with the convention $\bar{A}_N^{(\delta)}(t) = 0$ if no deep trap has been visited by time t .

On the one hand, we observe that both processes $A_N^{(\delta)}$ and $\bar{A}_N^{(\delta)}$ take the same values in the same order (namely the sequence of values of the successive deep traps visited by X). The holding times differ: for $A_N^{(\delta)}$, it is given by the occupation time of a deep trap; for $\bar{A}_N^{(\delta)}$ it is given by the increment of the clock process C_N between visits of deep traps. Thus we see that

$$\int_0^T |A_N^{(\delta)}(t) - \bar{A}_N^{(\delta)}(t)| dt \leq 2B_N^{-1} (\sup \tau_{N,x}) K_N^{(\delta)}(T) \tilde{B}_N^{-1} \int_0^{t_N C_N^{-1}(T)} \tau_{N,X_s} \mathbf{1}_{\tau_{N,X_s} \leq \delta B_N} ds,$$

where the sup is computed on the set of deep traps that have been visited by X before time $t_N C_N^{-1}(T)$ and $K_N^{(\delta)}(T)$ is the number of times $\bar{A}_N^{(\delta)}(t)$ changes its value before time $t_N C_N^{-1}(T)$.

(Let f and g be two functions defined on $[0, T]$ with values in a finite subset of \mathbb{R}_+ . Assume both f and g are piecewise constant, taking the values x_1, \dots, x_K in that order and with respective sojourn times w_1, \dots, w_K for f and ζ_1, \dots, ζ_K for g . Assume $\zeta_i \geq w_i$ for all i . Then f and g coincide except possibly on a set whose Lebesgue measure is smaller than $(\zeta_1 - w_1) + (\zeta_2 + \zeta_1 - w_2 + w_1) + \dots \leq K \sum_i (\zeta_i - w_i)$. Therefore the L_1 distance between f and g is bounded by $2 \sup_i |x_i| K \sum_i (\zeta_i - w_i)$.)

Both $B_N^{-1} \sup \tau_{N,x}$ and $K_N^{(\delta)}(T)$ are of order 1. To justify this last claim, we let $L_N^{(\delta)}(T)$ be the number of deep traps visited until time $t_N C_N^{-1}(T)$. On the one hand, we already know that $L_N^{(\delta)}(T)$ is of order 1. On the other hand $K_N^{(\delta)}(T) \mathbf{1}_{L_N^{(\delta)}(T) \leq k} = L_N^{(\delta)}(T) \mathbf{1}_{L_N^{(\delta)}(T) \leq k} \mathbf{1}_{\mathcal{F}_N^{(\delta)}(k)}$ for all k . As the probability of $\mathcal{F}_N^{(\delta)}(k)$ tends to 1, we deduce that $K_N^{(\delta)}(T)$ is of order 1 in probability.

As we already saw in the proof of (13.7), the expected value of

$$\tilde{B}_N^{-1} \int_0^{t_N} \tau_{N,X_s} \mathbf{1}_{\tau_{N,X_s} \leq \delta B_N} ds$$

tends to 0. Thus we conclude that

$$\limsup_{N \rightarrow +\infty} \mathbb{P} \left[\int_0^T |A_N^{(\delta)}(t) - \bar{A}_N^{(\delta)}(t)| dt \geq \eta \right] \xrightarrow{\delta \rightarrow 0} 0. \quad (14.4)$$

Let us now consider the difference $A_N - \bar{A}_N^{(\delta)}$: these processes do not necessarily take the same values, but they coincide when the process X is visiting a deep trap, i.e. $A_N(t) = \bar{A}_N(t)$ whenever $A_N(t) \geq \delta$. Therefore

$$\int_0^T |A_N(t) - \bar{A}_N^{(\delta)}(t)| dt \leq 2\delta T.$$

Combining this with (14.4), we get (14.3).

To conclude the proof of Theorem 14.1, it then only remains to show that $\mathcal{Z}^{(\delta)}$ converges to \mathcal{Z} as δ tends to 0. This is elementary. \square

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