ASIM: Solar Energy Availability Model for Wireless Sensor Networks

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***Abstract*—Solar irradiance prediction is a major issue in energy harvesting enabled WSNs. In this paper, we use Markov chains of increasing order to propose a new model - referred to as ASIM - for predicting solar irradiance patterns. Cornerstone of the proposed model is the determination of the state dependencies of the underlying Markov chains. The ASIM model is derived from a comprehensive solar radiation data set of four different locations around the globe. Our trace driven performance evaluation reveals that the ASIM model predicts the solar irradiance pattern very accurately - Normalized RMSE as low as 0.1 - as the order of the underlying Markov model increases. We also present mechanism to reduce the complexity of Markov chain to make the model more practical in wireless sensor networks.**

***Keywords*—Energy Harvesting, Solar Irradiance Prediction, Wireless Sensor Networks, Markov Chains**

I. Introduction

Solar harvesting in wireless sensor networks is challenged by solar irradiation availability at the generation point, which is highly time varying. Solar irradiation is diurnal in nature, maximum at noon and zero at night, and is highly affected by the current weather conditions. This behavior hinders the continuous supply of energy to the network nodes. This reveals the necessity for a mechanism with which the solar irradiation pattern may be predicted. Accurate predictions can lead to network protocol designs and battery charging-discharging methods which account priori for these time varying patterns, maximizing the network lifetime.

In this paper, we propose a new model to be used for predicting solar irradiation patterns. The model is based on Markov chains of increasing order. Markov chains are used in a number of ways to predict solar irradiance, however, accurate predictions are only possible if the state dependencies in the solar irradiance pattern are accounted for and correctly evaluated. The ASIM (Accurate Solar Irradiance prediction Model) model accounts for such dependencies and evaluates them based on a comprehensive radiations data set from various countries in the world. The results demonstrate that ASIM predicts solar radiation patterns with increasing accuracy as the order of the underlying Markov chain increases. To utilize ASIM model in WSN, we also present a reduced complexity version in which a Markov chain with order K = 3 provides the similar results as that of order 10.

The rest of the paper is organized as follows. In section II we review related work in this domain, in section III we describe the proposed model. In section IV we evaluate its performance using a comprehensive data set. Moreover, we present complexity analysis of the model in section V followed by Utilization of ASIM in section VI and finally in section VII we offer our conclusions and future research directions.

II. Related work

A number of solar energy availability models have been proposed recently. These models can be classified in three different categories: stochastic, statistical and machine learning based models. A brief review of these models is given below.

Many stochastic models of solar radiation availability make use of Markov chains [1], [2]. However, these models are restricted to first or second order Markov chains. A first order Markov chain model is proposed in [1] to generate synthetic series of global irradiation data for the design of photovoltaic systems. Similarly, a two state (active and inactive) first order Markov chain model is presented in [2] by combining the energy and traffic of the energy harvesting node.First order Markov chain models are also used in energy harvesting in Body Sensor Networks (BSN). For instance, authors in [3] present MAKERS a model for residual energy prediction in BSN. The MAKERS model relates the residual energy to the ambient energy availability, and so the residual energy predictions generated by the model are mapped to corresponding ambient energy values.

Higher order Markov chain based models have been proposed in literature to predict a number of time series data systems. In [4] first and second order Markov chain models are used to generate synthetic wind speed time series data. However, to our knowledge, higher order Markov chain models have not been used in WSNs to model and predict solar irradiance data sets. The proposed ASIM model fills this gap, as it incorporates high order Markov chains to predict solar irradiance time series to be used for the energy efficient operation of wireless sensor networks.

Statistical models use techniques like mean, variance, regression and moving average analysis. For instance, in [5], a statistical model is proposed to predict the mean value of solar radiation for any hour of the day. The model is derived by introducing a correction factor to previous mathematical models adopted by the same authors. The mathematical model proposed in [6] is based on improvements of the Bristow-Campbell [7] algorithm to estimate the daily solar radiation. Temperature, humidity and precipitation values are used to estimate the radiation. Alternative statistical approaches, such as Auto Regression (AR), Auto Regression Moving Average (ARMA), Auto Regression Integrated Moving Average (ARIMA) and Linear Regression (LR), are also tested on their ability to generate accurate predictions of solar radiations [8]. In WSNs, generally slight modifications of EWMA, such as presented in [9], [10] and [11] are used for solar energy predictions.

Machine learning methods are usually based on techniques such as neural networks and fuzzy logic. The authors in [12] propose a neural network model which is compared with existing models such as autoregressive and fuzzy logic models to predict half daily irradiance. The proposed model is found to outperform existing approaches with respect to the accuracy of the generated predictions. Similarly, the authors in [13] propose a prediction model which is developed by combining an artificial neural network (ANN) and a Markov transition model. A more recent work in [14] presents a hybrid model which is used to predict long term solar radiations. The model is a General Fuzzy Model (GFM) which uses a Gaussian Mixture Model (GMM) to predict solar radiation. However, machine learning models are usually slower and more prone to errors compared to stochastic models because those models require many features e.g. temperature, humidity, irradiance etc. Whereas ASIM requires only one feature the irradiance data to train itself. Additionally, the proposed ASIM model, stochastic in nature, thus enjoys a number of benefits such as fast convergence and good accuracy.

III. THE ASIM MODEL

In this section we review background theory on Markov chains and we describe how we use Markov chains of increasing order as a baseline to develop the proposed prediction model. Central elements of the proposed model are state dependencies of the underlying Markov chain which are determined using a comprehensive data set from different collection points around the world. The main characteristics of the data set are described together with information on how the model is implemented, tuned and validated.

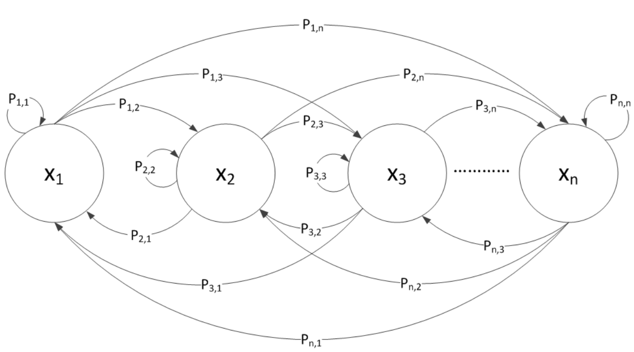

Fig. 1. Transition probabilities of the first order Markov chain

A. Description of ASIM Model

The proposed ASIM model is based on Markov chains of increasing order. We first describe a first order Markov chain with emphasis on the underlying state dependencies and we then describe how the first order chain can be extended to the k^{th} order case and how the increase in the order affects these state dependencies.

We consider a discrete time Markov chain $\{X_k\}$. The Markov chain is a discrete time random process with X_k denoting a random variable at the time instant k. Each random variable can attain values in the set $[x_1, x_2, ..., x_n]$. Each x_i is referred to as a state of the Markov chain. A first order Markov chain is known to possess the so-called Markov property, which states that the probability of the random process attaining a state at a particular time instant only depends on the attained state at the previous time instant i.e.

$$P(X_{k+1} = x_i \mid X_k = x_j, X_{k-1} = x_l, ..., X_1 = x_m) = \\ = P(X_{k+1} = x_i \mid X_k = x_j) = P_{j,i} \quad (1)$$

Note that we have used the notation $P_{j,i}$ to denote the transition probability from the state x_j to the state x_i. So, the random process can transition from any state to any other state, according to the latter transition probability. This is reflected in the relationship characterizing the probability $\Pi_i(k) = P(X_k = x_i)$ of the random variable X_k, at any time instant k, attaining the state x_i.

$$\Pi_i(k+1) = \sum_{j=1}^{n} \Pi_j(k) P_{j,i} \quad i, \in \{1, 2, .., n\} \qquad (2)$$

These state dependencies are depicted schematically in Fig. 1. In the ASIM model the states $[x_1, x_2, ..., x_n]$ are obtained by partitioning the range of attainable irradiance values into n equally sized sets. Each set corresponds to a state whose value is equal to the median of the set.

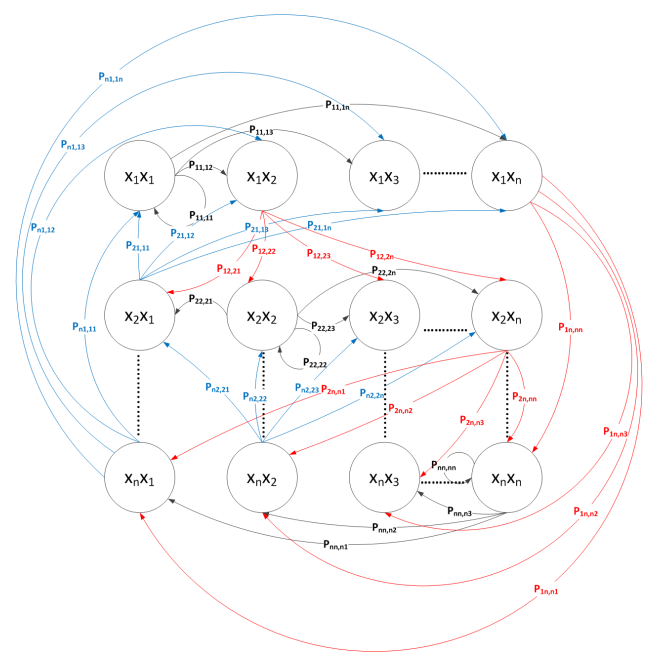

Fig. 2. Transition probabilities of the second order Markov chain

We now describe how we can extend the first order Markov chain to a second order Markov chain as an intermediate step in defining general K order Markov chains. A second order Markov chain has the property that the probability of the random process attaining a state at a particular time instant only depends on the attained states at the previous two time instant i.e.

$$P(X_{k+1} = x_i \mid X_k = x_j, X_{k-1} = x_l, ..., X_1 = x_m) = \\ = P(X_{k+1} = x_i \mid X_k = x_j, X_{k-1} = x_l) = P_{j,l,i} \quad (3)$$

Denoting by $\Pi_{j,l}(k) = P(X_k = x_j, X_{k-1} = x_l)$, the probability $\Pi_i(k) = P(X_k = x_i)$ is now evaluated according to:

$$\Pi_i(k+1) = \sum_{j=1}^{n}\sum_{l=1}^{n} \Pi_{j,l}(k) P_{j,l,i} \quad i, \in \{1, 2, .., n\} \quad (4)$$

In order to depict the above state dependencies schematically we consider all the 2-tuples of consecutive state transitions. We refer to each 2-tuple as a state. Transition from one state to the other is only admissible if the last element of the original state is the same as the first element of the destination state. For example, the state x_1x_2 can make a transition to any state starting with x_2, e.g. x_2x_3. The probability associated with the transition from x_1x_2 to x_2x_3 is the transition probability $P_{1,2,3}$. The state degeneracies of the second order Markov chain are shown schematically in Fig. 2. Similarly a general K order Markov chain can be defined using the second order Markov chain. A K order Markov chain has the property that the probability of the random process attaining a state at a particular time instant only depends on the attained states at the previous K time instant i.e.

$$P(X_{k+1} = x_i \mid X_k = x_j, X_{k-1} = x_l, ..., X_1 = x_m) = \\ P(X_{k+1} = x_i \mid X_k = x_j, X_{k-1} = x_l, ... \\ , X_{k-K+1} = x_q) = P_{j,l,..,q,i} \quad (5)$$

Denoting by $\Pi_{j,l,..,q}(k) = P(X_k = x_j, X_{k-1} = x_l, ..., X_{k-K+1} = x_q)$, the probability $\Pi_i(k) = P(X_k = x_i)$ is now evaluated according to:

$$\Pi_i(k+1) = \sum_{j=1}^{n}\sum_{l=1}^{n} ... \sum_{q=1}^{n} \Pi_{j,l,..,q}(k) P_{j,l,..,q,i} \quad i, \in \{1, 2, .., n\}$$

In order to understand the model, let us consider all the K-tuples of consecutive state transitions. We refer to each K-tuple as a state. Transition from one state to the other is only admissible if the last K element of the original state is the same as the first K element of the destination state. For example, the state $x_1x_2..x_3^K$ can make a transition to any state starting with $x_2..x_3^{K-1}$, e.g. $x_2..x_3^{K-1}x_5^K$. The probability associated with the transition from $x_1x_2..x_3^K$ to $x_2..x_3^{K-1}x_5^K$ is the transition probability $P_{1,2,..,3,5}$. We assume that the accuracy of prediction will improve as the value of K increases. We analyze this assumption in subsequent sections.

IV. Performance Evaluation and Results

In this section, we first present the utilized evaluation data sets followed by the evaluation methodology and performance analysis.

TABLE I. Data set information

Location	Mean Temp.	Data years	Daily total Radiation (W/m^2)		
			Max	min	average
Sonnblick, Austria	-04°C	1993 - 2012	3828	97	1450
Valentia, Ireland	11.4°C	2003 - 2012	3165	26	995
Bondville, IL, USA	11°C	2003 - 2012	3246	33	1470
Tamanrasset, Algeria	21.1°C	2001 - 2006	3604	1968	2809

A. Data Set Description

The model proposed in the previous section was tuned and evaluated using real world solar radiation data sets obtained from the World Radiation Data Center (WRDC) [15]. We considered data sets from four different locations in the world: Valentia (Ireland), Tamanrasset (Algeria), Bondville (Illinois, USA) and Sonnblick (Austria). These locations were selected, as the corresponding data sets are characterized by longer data collection period, variety in daily radiation and small number of missing values. Some basic characteristics of this data are shown in Table I. The data sets also exhibit varying level of dependency between radiation values. We performed basic autocorrelation analysis to estimate the level of dependency. The results of the autocorrelation analysis - not shown for brevity - suggest varying level of dependency.

B. Evaluation Methodology

To evaluate ASIM, we have used the first half of each trace as training data and the remaining half for testing the accuracy of the generated predictions. The states of the Markov chain are derived by partitioning the considered training data set into bins of size 100. For example, irradiance values in the range 0-99 are considered to lie within the first bin and are all assigned state one. The first Markov state thus contains all the radiance values in the range 0-99. The largest value of the data set determines the number of states in the Markov chain model i.e. if the largest value of the data is equal to 3604, as in the case of the Algeria data set, then the model comprises of 37 states.

In order to train the ASIM model, the steady state transition probabilities are extracted using the first half of the considered data traces. We calculate the steady state probability of a transition from a particular state to another state by dividing the number of transitions between these states within the considered data set, over all transitions. The trained model is then used to generate predictions for the next half of the trace. Once the system attains a particular state, the next state is predicted by considering the transition probabilities from the attained state, obtained during the training phase. The way that this is done is by partitioning the 0-1 interval into regions whose size is equal to the obtained transition probabilities. A random number is then generated according to a uniform distribution in the interval 0-1. The next state is dictated by the region into which this random number lies.

This methodology is employed to generate predictions for the second half of each data set. The accuracy of the predictions and thus the effectiveness of the prediction algorithm is evaluated by comparing the predicted data with the real world data.

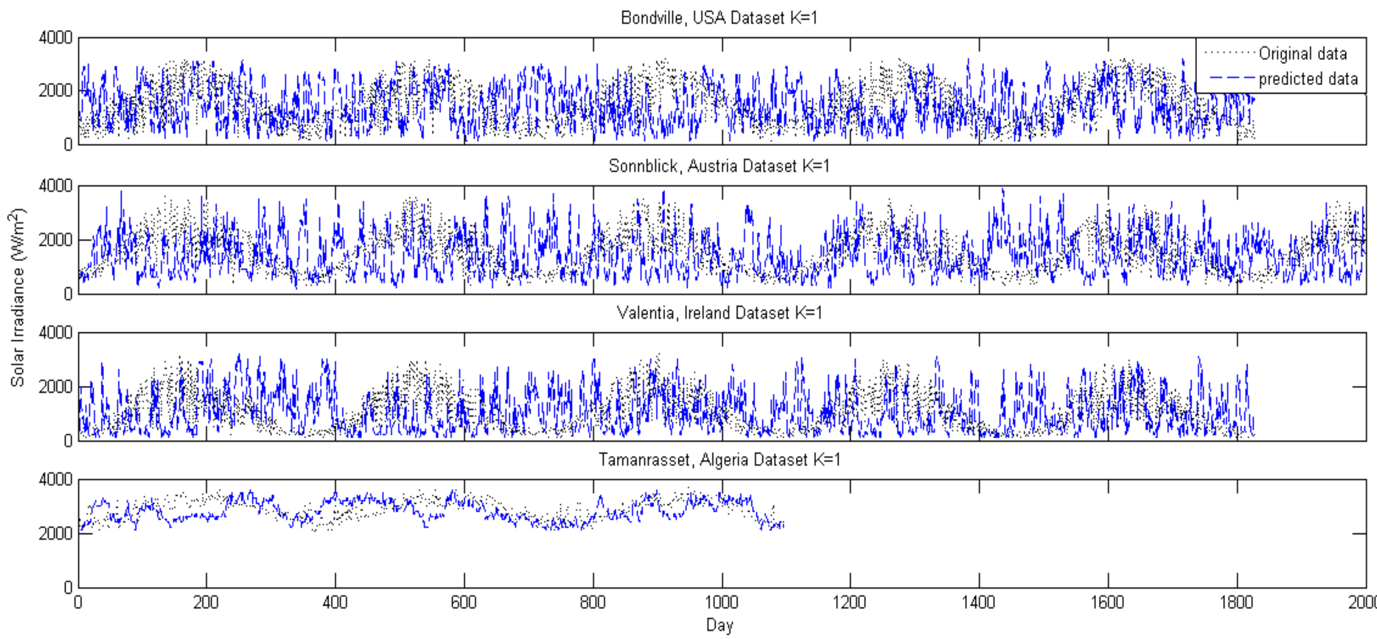

Fig. 3. Comparison between original and the predicted data for K=1

C. Evaluation Results

We present the evaluation results in increasing order of model complexity. We first start with a first order Markov chain model (K=1) and in order to investigate the effect of increasing the order of the underlying Markov chain we present the 5th and 10th order cases. Although we have performed analysis for other values of K, these results are representative of all other values of K. The evaluation is conducted by comparing predicted and real values utilizing graphs showing both quantities over time. In addition we use two performance metrics: the Normalized Root Mean Square Error (NRMSE) and the number of predicted points which lie under one standard deviation from the corresponding original point of the original data set. The former is a measure of the error rate while the latter depicts the closeness of the predicted values to the original values, in other words the accuracy of the ASIM model. The results of these measures are discussed in the forthcoming sections. The NRMSE is defined as:

$$Error = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\frac{actual_i - predicted_i}{actual_i})^2} \quad i, \in \{1, 2, .., N\} \tag{6}$$

where N is the total number of predicted values.

1) First Order Markov chain Model: This is the simplest form of the ASIM model where each state depends only on the previous state. In Fig. 3 we show four graphs each of which compares real and predicted data for the considered locations. The graphs depict the time evolution of the real and predicted Markov states of the solar radiation system. The x-axis represents the time (in days) and the y-axis axis represents the Markov states at each day.

The results in Fig. 3 indicate that the predicted values do not match very well with the original data. This demonstrates the inability of the first order Markov chain model to correctly capture the underlying state dependencies and thus generate accurate predictions. This is also demonstrated in Table II which shows the number of points which lie under one standard deviation of the corresponding original values. For the first order Markov chain model we observe that only 50% of the predicted values lie within one standard deviation. Higher number of points below the one standard deviation are needed to indicate good level of prediction accuracy and this motivates the investigation of higher order Markov chains despite the increased implementation complexity. The low levels of prediction accuracy of the first order model are also supported by the low values of the root mean squared error which are depicted in Table III. This further warrants the use of a higher value of K.

2) Higher Order Markov chain Model with K = 5: In order to investigate the prediction accuracy of higher order models we consider a Markov chain Model with K=5 which implies that the next state depends on the previous 5 states. In ASIM, this is implemented by defining a new set of states where each state is a combination of states of the first order Markov chain Model. This refinement in the chosen set of states allows for a more detailed description of the underlying state dependencies which in turn leads to higher prediction accuracy. This is demonstrated in Fig. 4 which shows the time

TABLE II. POINTS BELOW ONE STANDARD DEVIATION

Location	Total points	Points under one standard deviation		
		K=1	K=5	K=10
Sonnblick, Austria	3651	1826	2014	2699
Valentia, Ireland	1827	923	951	1329
Bondville, IL, USA	1827	923	1344	1359
Tamanrasset, Algeria	1096	494	547	891

evolution of the states of the solar radiation at the locations under investigation. It is evident that the predicted values are in much more agreement with the actual values relative to the

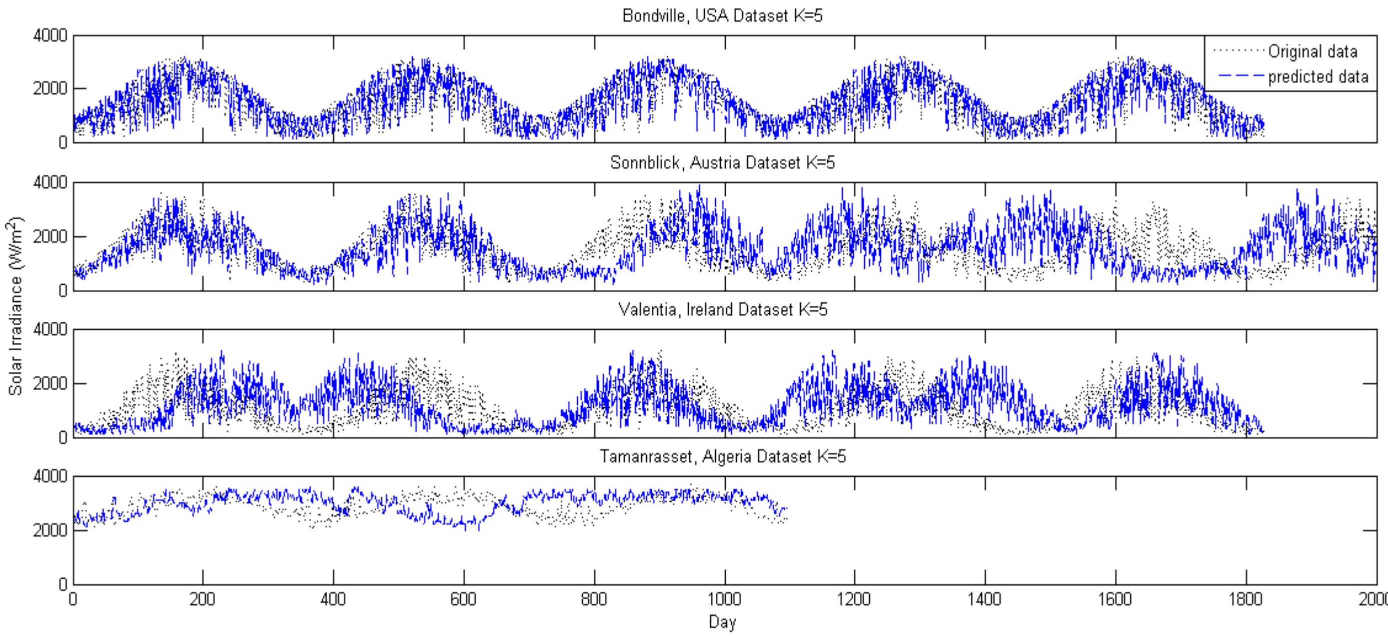

Fig. 4. Comparison between original and the predicted data for K=5

first order model case. This is also indicated by the lower root mean square error values which are shown in Table III and the higher number of points under one standard deviation from the actual value of the original data which is highlighted in Table II. However, the diurnal behavior of the solar irradiation data is not captured correctly by the considered models, except in the case of Bondville, USA. For Bondville, USA, it seems that a value of K = 5 is good enough to be used in practice. The autocorrelation analysis presented in the previous section can be used to explain this as the Bonville data set is characterized by low autocorrelation values which converge relatively fast. For all other locations, it is evident that higher order Markov models are needed to provide the required accuracy. However, the goal of the ASIM model is to provide a generic solution which can be used to predict solar radiation values and thus higher order Markov chain models are necessary.

3) Higher Order Markov chain Model with K = 10: In the case of K = 10, each derived state now comprises of 10 basic states of the first order model. Fig. 5 shows real solar radiation values and predicted values generated by the 10th order ASIM model for the locations under consideration. The results indicate good agreement between real and predicted values in all cases and the ability of the ASIM model to capture the diurnal nature of the solar radiation data. This is supported by the results of Table II which indicate that up to 81% of the predicted values lie within one standard deviation away from the actual value of the original data. The higher accuracy of the generated predictions is also indicated by the results of Table III. The table shows that the 10'th order model achieves the smallest normalized means squared errors with the minimum value being 0.1 corresponding to the Sonnblick data set, and the maximum value being 1.36 which corresponds to the Algeria data set. An average value of 0.78 has been achieved.

TABLE III. NORMALIZED RMSE

Location	Normalised RMSE		
	K=1	K=5	K=10
Sonnblick, Austria	1.39	1.38	0.68
Valentia, Ireland	3.36	2.83	0.99
Bondville, IL, USA	2.65	1.4	1.36
Tamanrasset, Algeria	0.2	0.18	0.1

V. COMPLEXITY ANALYSIS OF ASIM

In the previous section, we have shown that ASIM is capable of predicting solar irradiance value with reasonable accuracy. We have also seen that the accuracy of model increases with an increase in the order of Markov Chain up to K=10. An increase in K beyond 10 has marginal or no impact on the accuracy of prediction. This is shown in Figure 6. However, the Markov Chain order K=10 results into a

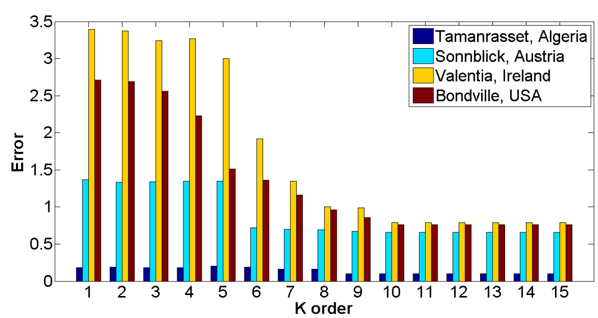

Fig. 6. K order vs. No. of NRMSE

fairly complex structure due to a very large number of states involved which may deem the ASIM model impractical. This warrants an analysis of state complexity and possible reduction in number of states without losing significant accuracy. In ASIM, the number of states are governed by the equation given

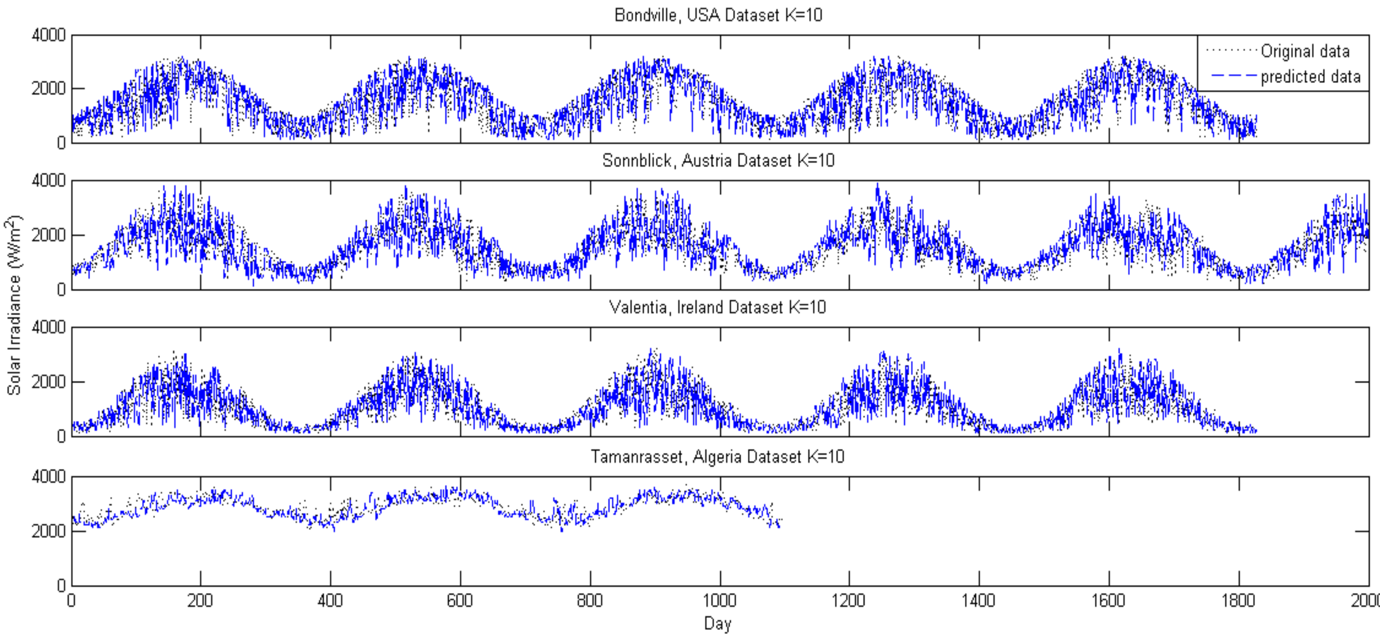

Fig. 5. Comparison between original and the predicted data for K=10

below

$$N = \left(\frac{D_{max}}{W}\right)^K \quad (7)$$

where N is the total number of states, K is the order of Markov chain, D_{max} represents the maximum irradiance value for the given location and W is the bin size which refers to the range of irradiance values lying in a single state. Equation (7) suggests that a linear increase in the order of the Markov chain K results in an exponential increase in the number of states. A linear decrease in the bin size W also increases the number of states. While decreasing K and increasing W in isolation may result into a Markov chain with small number of states, it is not guaranteed to provide accurate predictions. Considering both the variables simultaneously is expected to provide optimal regions where the number of states is small and the accuracy is also acceptable. In order to demonstrate this, we compare the complexity and accuracy of two scenarios: one with K=3 and W=5 and the other one with K=10 and W=100. The first scenario is characterized by smaller complexity as it requires a smaller number of states to be implemented. The accuracy achieved by the two models is

TABLE IV. NORMALIZED RMSE

Location	Normalized RMSE	
	K = 3 w =5	K = 10 W =100
Sonnblick, Austria	0.738	0.68
Valentia, Ireland	1.132	0.99
Bondville, IL, USA	1.68	1.36
Tamanrasset, Algeria	0.0982	0.1

evaluated based on the NRMSE and one standard deviation measurements. Table IV shows the Normalized RMSE for both ASIM models (complex with K=10, W=100 and reduced complexity with K=3, W=5). It can easily be observed from the table that the two models achieve similar error values. The Algeria data set is of particular significance as the reduced complexity ASIM model reports smaller error. This means that reduction in the implementation complexity can in some cases lead to improved accuracy. This is also demonstrated in the One Standard Deviation results summarized in table V. For the Ireland data set, the reduced complexity ASIM model has improved the accuracy up to 5.75%. In order to compare

TABLE V. ONE STANDARD DEVIATION ANALYSIS

Location	Total Points	Poins under one Standard Deviation		Improvement Percentage %
		K = 3 w = 5	K = 10 w = 100	
Sonnblick, Austria	3651	2724	2699	0.68
Valentia, Ireland	1827	1434	1329	5.75
Bondville, IL, USA	1827	1340	1359	-1.04
Tamanrasset, Algeria	1096	902	891	1.0

the complexity of the two models, in table VI we show the number of states corresponding to each model. Given that the maximum data value is 3800, the complex ASIM model requires $6.278\text{x}10^{15}$ states for its implementation, whereas the reduced ASIM model with K=3 and W=5 requires $4.389\text{x}10^{8}$. This demonstrates that the reduced complexity model requires $1.43\text{x}10^{7}$ times less states than the complex ASIM. In the future, we aim at further investigating the complexity issue and find ranges of (K,W) duple which achieve high prediction accuracy and low implementation complexity.

VI. UTILIZATION OF ASIM IN WSNS

Application fidelity and virtually infinite life time are two desired but conflicting features of wireless sensor networks. In traditional sensor networks, it is not possible to achieve both because of limited power supply. Sensor networks harvesting energy from ambient sources and making use of accurate energy prediction models - such as ASIM - can potentially achieve both the objectives. For illustration purposes, we outline such a mechanism for a few applications below.

TABLE VI. COMPLEXITY REDUCTION IN TERMS OF TOTAL NUMBER OF STATES

Order K	Bin size W	Dmax/W	Total States	X times Reduction
10	100	(3800/100)	6.27x10^{15}	1
3	5	(3800/5)	4.38x10^{8}	1.43x10^{7}

Consider an energy aware routing protocol. Typically, path selection in such protocols is dictated by residual energy in a node or set of nodes. Since state of the art protocols do not take advantage of accurate prediction of future state of harvested energy, only viable option to maintain longer life time is to use a sub-optimal path - compromising application fidelity. If the routing algorithm is aware of energy to be harvested in future along with residual energy level, it can choose a node as next hop even though the node may appear to have scarce energy.

Similarly, consider a topology control protocol where the objective is to maintain connectivity between all the nodes all the time even though the residual energy reduces gradually. The application fidelity in this case is level of connectivity. As the energy level in nodes goes down, in traditional networks, the level of connectivity also goes down to maintain longer life time. If topology control protocols are aware of future prospects of energy to be harvested, they can still maintain high level of connectivity even though current energy levels are low.

Apart from improving application fidelity, accurate energy availability models like ASIM can also be used prior to the deployment of sensor networks. For instance, based on study of solar availability characteristics of a particular geographic location and application requirement, an optimal battery can be designed.

VII. CONCLUSION AND FUTURE WORK

In this paper, we propose ASIM, a prediction model for solar radiation which is based on higher order Markov chains. We have used real world data sets at four different locations around the world to train and evaluate our model. It is observed that as we increase the order of the underlying Markov chain the accuracy of the prediction also increases and that a 10th order model is adequate to generate predictions of reasonable accuracy. Higher order Markov chains (beyond K=10) are not observed to improve the prediction performance of the model. The 10^{th} order model achieves an accuracy of 81% and an average normalized root mean square error equal to 0.78 with the minimum reaching a value 0.1. In the future, we aim at extending our model to be used for other types of data sets, we aim at reducing the implementation complexity of the system without compromising the achieved performance and accuracy and we aim at integrating the approach in the design of harvesting enabled WSNs demonstrating its beneficial effects in extending the network lifetime.

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