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BRIEF COMMUNICATION

Forecast of solar power: a key to power management and environmental protection

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Abstract Power management through the day and through different seasons in the year is a major challenge in cities around the world as the power generation is from a mix of resources. It is difficult to predict, a priori, the yield from renewable resources on a particular day to tune the fossil fuel fired generators leading to less control of atmospheric pollution from these plants. In this paper, we present a model to predict the yield from a solar photovoltaic (SPV) plant based on the weather forecast in the location. This model can be deployed in the management of distributed energy generation system consisting of SPV systems. The deviations of this model from the measured values are <15 % for most of the days. The methodology adopted in arriving at this model can be used in any location. This model is simple to use as it uses performance data from a SPV plant in a location and the weather forecast data available in the public domain. Hence, it would be a powerful tool for private solar power producers availing net-metering facility.

Keywords Prediction of yield · Solar photovoltaic system · Multivariate regression · Power management

Introduction

The performance of a solar photovoltaic (SPV) system depends on the solar radiation flux which is a function of many site-specific factors such as latitude, season, cloudiness and air pollution. It is difficult to foretell, a priori, the yield from SPV parks at a location. Hence a detailed analysis of the performance of SPV systems is needed to provide valuable information for predicting the yield from such systems.

The yield from a SPV module also depends directly on their photo-conversion efficiency. The efficiencies of the modules depend on the module temperature. The efficiency of the modules with cooling was 13 %, while for the modules without cooling it was 10 % (Conserval Engineering Inc. 2015). This kind of cooling will occur in different seasons in a year and the yield from the SPV systems changes accordingly. The performance evaluation of a SPV system in South Eastern Italy, with monocrystalline silicon panels (Congedo et al. 2013), indicates the highest and lowest efficiencies of 17 and 15 % in spring and summer, respectively.

In Germany, the electricity mix comes from sources like coal, nuclear, gas, wind, solar, biomass and hydro-power stations (Fraunhofer Institute for Solar Energy 2014). Since electricity is generated from multiple sources, there is, at times, wastage because all sources feed into the same grid a certain planned amount of electricity which could surpass the demand. The electricity demand varies through the day, week and year (Gridwatch 2015) (Energy Institute of Haas 2015) as seen in the UK Gridwatch. Here also, electricity is generated from multiple sources like coal, nuclear, combined cycle gas-turbine (CCGT), wind, biomass and others. In addition, UK imports electricity from neighbouring countries. In a day, from mid-night to mid-day, there is an increase in demand of almost 49 %. This variation in demand is met by mainly increasing production from coal-fired and CCGT stations. Similar situation is faced by California electricity demand and supply (California Energy Commission 2015).

Most of the countries are slowly moving towards seeking sustainable energy production and reduction of greenhouse

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gas (GHG) emission (Panwar et al. 2010). Hence, renewable energy sources (RES) play a very important role in distributed energy generation (DEG). Although low emission power generation is possible through RES, they are capital intensive and fluctuating in nature. Practically, a sudden or a complete departure from fossil fuels is not possible (Priya and Bandyopadhyay 2013) and hence, the RES remain as a subsidiary for the conventional energy sources which are mainly powered by fossil fuels. The power demand at a location will be a mix of power from many resources (Ho et al. 2013) which can be represented as

$$P = aP_{\mathrm{F}} + bP_{\mathrm{S}} + cP_{\mathrm{W}} + dP_{\mathrm{O}}, \quad (1)$$

where P_{F}, P_{S}, P_{W} and P_{O} are the installed capacities of fossil fuel fired plants, solar installations, wind parks and other sources like CCGT or imports, respectively. a, b, c and d are the percentage utilizations that are needed to meet the power demand. When b and c are high, a and d could be reduced, decreasing the polluting gases.

There is a serious problem of finding ways to meet the energy needs consistently without wastage. SPV systems are dependent on environmental variables outside of human control and there is no way to generate more or less electricity based on demand, unless SPV systems are partially shut down when there is excess electricity generation. Hence, it is very essential to forecast the yield of SPV systems. It is highly beneficial because it assists the utility in unit commitment analysis, reserve requirement estimation, contingency analysis, framing electricity bidding strategies and solving voltage issues that arise from grid integration of SPV system (Zhang et al. 2015b). Prediction models were developed for forecasting power output of SPV systems, which played a major role in energy resource management. In 2014, prediction models for power output and energy efficiency were developed using a grid-interactive rooftop photovoltaic (RTPV) system installed on an institutional building located in Macau. These models were validated using measured data of other grid-connected PV systems of Macau. One of the prediction models used for system efficiency was based on the ratio of the predicted output power to the predicted solar irradiance. This ratio model was able to fit the intermediate phase (9 a.m. to 4 p.m.) very well but not accurate for the growth and decay phases (Su et al. 2012).

In 2013, a study conducted on a PV installation located in Belgium, consisting of four different technologies, monocrystalline, polycrystalline, micro amorphous and monomorphic SPV modules, proved that module temperature is majorly affected by ambient temperature and irradiation. A mathematical expression was derived to predict the yield on DC side of SPV systems. This expression takes into account, the area per $\mathrm{kW_p}$ of SPV, solar irradiance, transmission-absorption factor, module temperature and temperature coefficient at maximum power point. This model had a maximum deviation of 15 % from the measured values. According to this study, module temperature is less affected by wind temperature, wind velocity and humidity (Verhelst et al. 2013).

A study conducted on a zero energy building (ZEB) of Singapore, with installed SPV capacity of 190 $\mathrm{W_p}$ concluded that polycrystalline type of SPV is the most productive variety of all PV technologies for SPV installations under tropical climate. The annual average daily performance profile of this SPV system was modelled using one of the popular simulation tools and the most accurate model was then used to forecast the annual energy yield under different scenarios. This model fairly predicted the annual average output power of modules. This study also concluded that precision of the model can be improved by taking the energy losses in the module into account and usage of more realistic weather data (Saber et al. 2014).

There are several open-web tools which predict the power output of SPV systems installed at any location. These tools use historic data of power generation and weather of a specific location to predict the SPV output (Iyengar et al. 2014). The concept of artificial neural networks and fuzzy logic has facilitated development of forecast models for incident solar radiation and solar power output. The error in the results obtained from these models was found to be less than the conventional models, mainly due to their capability in depicting behaviour of non-linear and time-varying inputs such as meteorological parameters (Chen et al. 2013; Hocaoglu et al. 2008; Paoli et al. 2010). Although these models are good, they are complex. Hence, it would be much beneficial to adopt a hybrid model which involves the major parameters which cause attenuation of solar radiation at upper atmosphere and solar power output at module level. Net-metering mechanism at household level being the recent trend in developing countries (Mer et al. 2015; Thakur and Chakraborty 2015), it is important to arrive at a forecast model which can be conveniently used by the end-users also. This model must deliver the yield of an SPV system using the forecast data available on public domain and must be simple to use.

In this paper, we establish an empirical relationship between the yield of a SPV system and the atmospheric conditions, based on the performance of a grid-interactive 20 $\mathrm{kW_p}$ SPV system with polycrystalline silicon PV modules installed at a location in tropical belt of India. The power generation patterns from the SPV system during various seasons corresponding to changes in weather conditions are studied. Using multivariate regression, a best fit expression is obtained which can predict, in advance, the expected yield from a SPV system given the weather conditions. The effect of climatic parameters such as cloud cover fraction, aerosol optical depth, humidity and ambient temperature were analysed and accordingly used to predict the yield of the SPV system. The predictions of this nature are useful in management of power systems consisting of multiple resources. In many parts of the world, power supply to towns and cities comes from multiple sources. If the yield from SPV systems is known in advance, the generation from coal-fired thermal stations can be moderated and thus control the emissions into the atmosphere.

Experimental details

An SPV system of capacity 20 kW_p was commissioned in April, 2013. The system partially powers the Main Administrative Building of Indian Institute of Science which is over 100-year old and is identified as a Heritage Site. Ariel view and single-line diagram of the SPV system are as shown in Fig. 1a, b. The SPV modules are oriented towards the south with an inclination of 13°, which is the latitude of the location. A remote monitoring system records the real-time data. The global horizontal irradiance (GHI), power output and module temperature data are collected at an interval of 5 min. The weather data are collected using Davis Vantage Pro2 weather station.

Results and discussion

Performance of the SPV system

The monthly yield of the SPV system during 2013–2014 is shown in Fig. 2a. The highest monthly yield was in March (3132 kWh) and the least in July (1579 kWh) corresponding to summer and monsoon months, respectively.

(a)

(b)

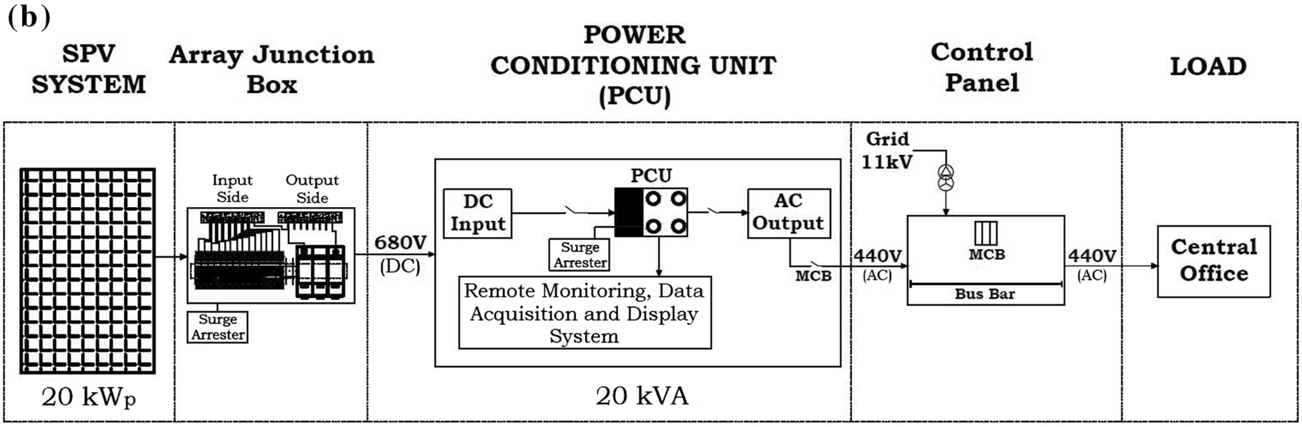

Fig. 1 20 kW_p grid-interactive SPV system. **a** Ariel view of the SPV system. **b** Single-line diagram of the SPV system connected to the load through a power conditioning unit (PCU) of rating 20 kVA

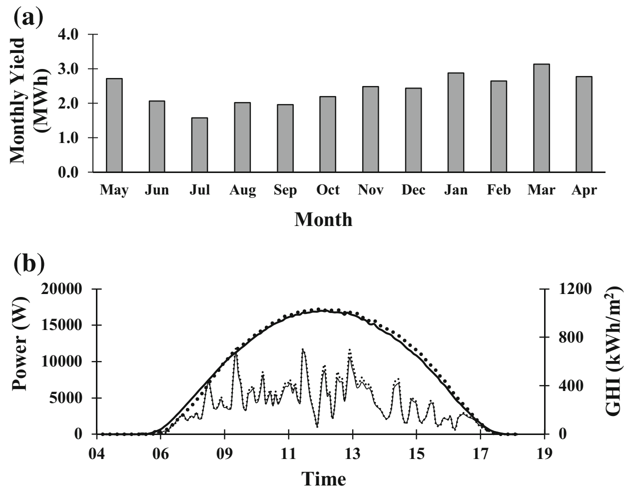

Fig. 2 Generation patterns of the SPV system. **a** Variation of monthly yield. **b** Variation of power as a function of time for a clear day (*thick line*) and a cloudy day (*thin line*). *Dotted line* denotes GHI and *solid line* denotes power generated

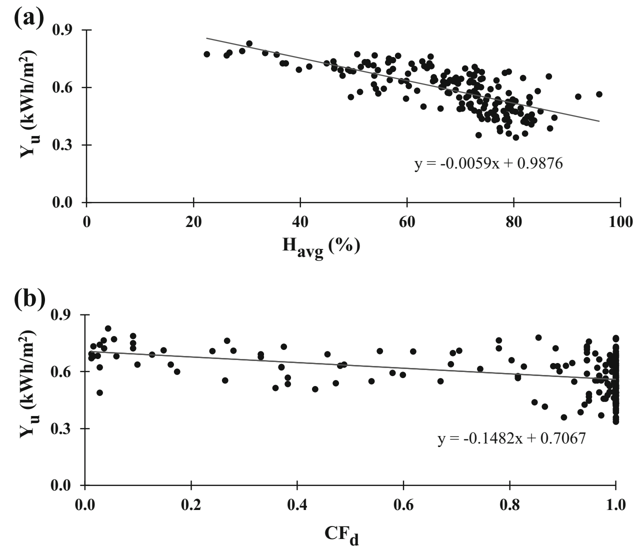

Fig. 3 Variation of Y_u corresponding to CF_d and H_{avg}. **a** Y_u as a function of CF_d for the day taken from MODIS/Aqua satellite. **b** Variation of Y_u with H_{avg}

The net annual yield during this period was 28.9 MWh and has avoided 23 tonnes of CO_2 emission into the atmosphere in 1 year, assuming CO_2 emission to be 800 g per kWh for a coal-fired thermal plant (Reichelstein and Yorston 2012).

The variation of power generated by the SPV system during the day is plotted in Fig. 2b, along with the instantaneous GHI (I_i) for a clear sunny and a cloudy day. The power generated follows the variation in I_i. The capacity utilization factor (CUF) is an indicator of the overall performance of the SPV system. The CUF of a SPV system is the ratio of actual energy generated in a day to the energy generated if the system works 24 h a day (Bridge to India 2015). CUF of this SPV system is 16.5 % that is well within the range of average CUF of the rooftop SPV systems in India, which is 16–17 % (National Renewable Energy Laboratory 2011). CUF is location dependent. For instance, the average CUF of SPV system located in Arizona, USA is 24 %, whereas in Massachusetts, USA, it is 18 % (Treehugger 2013). A photovoltaic park of capacity 171.36 kW_p installed in Sitia, Crete has a CUF of 15.26 % (Kymakis et al. 2008). The CUF of the system is mainly dependent on the GHI at the location and energy conversion efficiency of the SPV modules. GHI at the surface depends on the cloud fraction and atmospheric constituents, mainly humidity and aerosols.

Climatic parameters

Cloud cover fraction

The cloud cover fraction (CF) is a very important criterion in the selection of location for a SPV system. The clouds reflect large fraction of the solar radiation back into the space and reduces the transmitted solar radiation that reaches earth's surface (Ramanathan et al. 1988). In the presence of clouds, direct component of solar radiation tends to decrease, while diffuse component increases depending on the optical thickness of the cloud (Pfister et al. 2003). The simple equations to calculate the effect of CF on incident solar radiation found in the literature (Molg et al. 2008) are insufficient to explain radiation loss in the atmosphere. Daily average CF (CF_d) data are available from MODIS/Aqua satellite over 10 km^2 area around Bangalore (Earth Observation 2014). The CF_d thus obtained is plotted against the yield per unit area (Y_u) of a day from the SPV system in Fig. 3a. As CF_d increases, Y_u decreases indicating the reduction in daily GHI (I_d).

Humidity

Absorption bands of water vapour occur primarily in near-infrared regions (Eldridge 1967). In addition, there is scattering and reflection of radiation from the surface of water droplets (Gwandu and Creasey 1995). Thus, humidity in the atmosphere affects the GHI that falls on SPV modules. The daily average humidity (H_{avg}), as measured at the location, in winter was 56 %, in summer 48 %, during post-monsoon 71 % and during monsoon 75 %. This seasonal variation in H_{avg} affects the yield from SPV system. As shown in Fig. 3b, Y_u decreases with increase in H_{avg} and there is a strong correlation between these factors.

Aerosols

Aerosols are minute suspended particles that can block solar radiation. Aerosol optical depth (AOD) data could not be obtained for cloudy days. Even for clear days, there is a

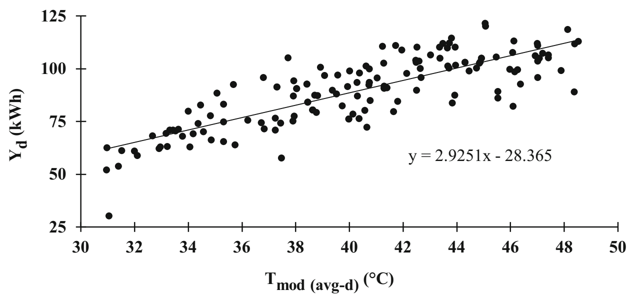

Fig. 4 Variation of Y_d corresponding to $T_{mod(avg\text{-}d)}$

large scatter in the data and no correlation between yield and AOD in the location could be established. Hence, the effect of AOD has not been considered in this study.

Module temperature

One of the necessary conditions for a SPV system to deliver 100 % of its installed capacity is that the temperature of SPV modules and radiation flux are maintained at rated values. The performance of the SPV system is primarily dependent on the module efficiency. As the module operates over a wide range of temperatures throughout the year, its power conversion efficiency is strongly affected by instantaneous module temperature, unless it is maintained at 25 °C (Nishioka et al. 2003). For a module installed in a field or on the rooftop of a building, the module temperature at which the module attains maximum efficiency varies with seasons and the module efficiency is known to decrease with increase in module temperature (Tina and Scorfani 2008; Vasisht et al. 2016). However, the daily yield (Y_d) is the summation of power output of the day, which is dependent on solar insolation and module temperature. Figure 4 shows the variation of Y_d corresponding to daily average instantaneous module temperature ($T_{mod(avg\text{-}d)}$). On clear days, the modules attain higher temperatures and the yield is also higher. This shows that module temperature and yield are collectively influenced by prominent climatic variables such as solar irradiance (Ramachandra and Shruthi 2007), albedo (Andrews and Pearce 2013), duration of sunshine (Armstrong and Hurley 2010; Singh and Banerjee 2015), wind, humidity (Mekhilef et al. 2012), precipitation, dust (Darwish et al. 2015), etc. These parameters are season dependent and hence, yield of the SPV system on a particular day is a combination of many factors in addition to module temperature.

Empirical equation

From this study, it is apparent that long sunshine periods during summer and post-monsoon months produce higher yield, while high ambient temperature in this period reduces the module efficiencies compared to winter and monsoon months. Besides, as already discussed, Y_d of the system is dependent on CF_d and H_{avg} in the atmosphere because of their effect on I_d. These factors also have a seasonal variation; for instance, the AOD is low, while the H_{avg} is high during monsoon season. During winters, I_d is low because of shorter days and so are $T_{mod(avg\text{-}d)}$. Similarly, during summers, I_d and $T_{mod(avg\text{-}d)}$ are high. To understand the influence of various factors on the overall output of a SPV system, a multivariate regression is carried out using the data from the system to come up with a consolidated expression, which is of the form,

$$\text{Yield} = K + \alpha V_1 + \beta V_2 + \gamma V_3 + \delta V_4, \tag{2}$$

where K, α, β, γ and δ are constants and V_1, V_2, V_3 and V_4 are the variables. The inputs for the regression are Y_u, $T_{mod(avg\text{-}d)}$, H_{avg}, daily extra-terrestrial radiation (ETR_d) and CF_d at the latitude/longitude of the location. ETR_d at the location was used instead of I_d because ETR_d calculations are accurate and are easily available. AOD data for all the days were not available and hence are not considered as a variant in the regression. Twelve days in each month from May 2013 to September 2014 were randomly chosen and the regression equation obtained is

$$\begin{aligned} Y_{u(c)} = 0.3066 &- (0.01631 * ETR_d) \\ &+ \left(0.01515 * T_{mod(avg-d)}\right) - \left(0.001972 * H_{avg}\right) \\ &- (0.0262 * CF_d). \end{aligned} \tag{3}$$

Two other days in each month, which were not considered for regression, were picked for validating the derived equation. The calculated yield ($Y_{u(c)}$) for these days is computed and compared with measured yield (Y_u), as shown in Fig. 5a. Deviation from this expression for most days is under 15 % and for a couple of days it is as high as 18 %. The large error is mostly for a few days with low I_d due to extreme weather conditions like high CF_d or H_{avg}. Accuracy of CF_d at the location may also add to the deviation in estimating $Y_{u(c)}$. The deviation is found to be minimum during post-monsoon and early summer periods which may be attributed to clear skies. Figure 5a also shows the pattern of maximum and minimum Y_u of each month. The variation of maximum Y_u shows the ideal pattern of generation, which would be a function of optimal values of module temperature, humidity and CF, so as to produce the highest possible yields. During the days of post-monsoon and early summer, the values of module temperature, humidity and CF are optimal, thus leading to maximum Y_u.

Figure 5b shows the calculated and observed yield for January and February 2015, which lies outside the period considered for regression. Only for 3 days, the deviation is found to be over 15 % with maximum deviation of 18.5 % indicating that Eq. (2) holds good for any period of time.

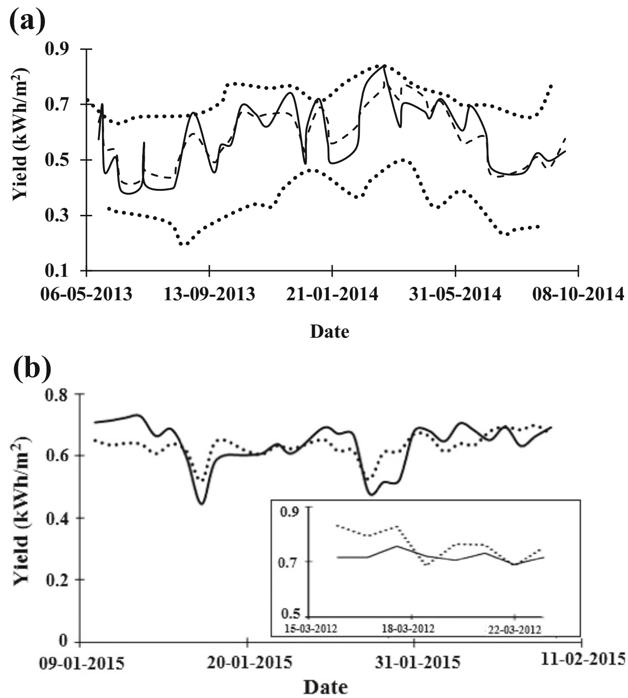

Fig. 5 Regression curve: a Y_u (*solid line*) and $Y_{u(c)}$ (*broken line*). The daily maximum and minimum Y_u in the month are shown by *dotted lines*. **b** Y_u (*solid line*) and $Y_{u(c)}$ (*dotted line*) for January/February 2015. *Inset* Y_u (*dotted line*) data from a different SPV system and $Y_{u(c)}$ (*solid line*)

One week's data from another SPV system installed in Bangalore that had modules with rated efficiency of 11 % became available. The yield from this plant is scaled with the ratio of the observed average efficiency of the known SPV module and the rated efficiency of the unknown module. The scaled yield and the yield calculated from Eq. (3) are compared in the inset of Fig. 5b. For one day, the deviation is 15 % and for all other days the deviation is under 10 %. Thus, it is possible to rewrite Eq. (3) as

$$\begin{aligned} Y_{\mathrm{u(c)}} = {} & [0.3066 - (0.01631 * \mathrm{ETR_d}) \\ & + (0.01515 * T_{\mathrm{mod(avg-d)}}) - (0.001972 * H_{\mathrm{avg}}) \\ & - (0.0262 * \mathrm{CF_d})] * (\eta_{\mathrm{RP}}/\eta_{\mathrm{RU}}), \end{aligned} \tag{4}$$

where η_{RP} is the average efficiency of the reference SPV system and η_{RU} is the rated efficiency of the unknown SPV system.

Most of the countries around the world have weather forecasting models that can predict the atmospheric conditions for about 48 h quite precisely. In recent times, several models have been developed for forecasting multi-level CF (Shah et al. 2015; Paoli et al. 2015), solar radiation (Pelland et al. 2011), ambient temperature and humidity (Kumar et al. 2015). In addition to these, weather forecasts are available on the public domain, which are normally precise and reliable. Hence, by obtaining data on one SPV installation in a location and deriving an empirical equation of this type, it is possible to predict the yield from any SPV system in that location in advance.

In most of the SPV systems, module temperature is not recorded. On one system if module temperature data are collected, a relationship between $T_{\mathrm{mod(avg\text{-}d)}}$ and daily average ambient temperature ($T_{\mathrm{amb(avg\text{-}d)}}$) can be derived for the location that can be used for prediction. In the present study, $T_{\mathrm{mod(avg\text{-}d)}} = 1.54 * T_{\mathrm{amb(avg\text{-}d)}}$ relation fitted the curve and with the calculated $T_{\mathrm{mod(avg\text{-}d)}}$, only four data points showed a deviation of around 20 %. The ratio ($T_{\mathrm{mod(avg\text{-}d)}}/T_{\mathrm{amb(avg\text{-}d)}}$) may differ for locations having non-tropical climate.

With this kind of prediction, when multiple resources are used for generation of electricity, the power generation from other sources can be tuned for maximum efficiency and minimum pollution. For example, if the weather prediction is clear skies with a specific amount of humidity and CF, the yield from all the SPV systems in that location can be predicted. Based on the weather prediction, even 24 h in advance, quite a bit of fossil fuel usage can be prevented because the term *b* in Eq. (1) would be known. There have been many models (Fard et al. 2016; Zhang et al. 2015a) to predict power that can be generated from a wind turbine and hence the term *c* in Eq. (1) is also known. Thus, the terms *a* and *d* can be fine-tuned and the thermal power plants using fossil fuels can be used at minimum levels.

Conclusion

Power management at a location offers many challenges as it is a mix from different sources and all the power stations end up generating more power than required. There is a huge wastage of power leading to burning fossil fuels unnecessarily. In order to optimize usage of the fossil fuel fired thermal stations, it is important to predict the power generation from other resources like solar and wind plants. To predict the yield from a solar plant, it is shown that the weather conditions play an important role. An empirical relation between climatic conditions (like humidity, CF and temperature) and the yield from an SPV system is derived using data from a 20 $\mathrm{kW_p}$ SPV system. It is observed that the yield from the SPV system decreases linearly with increase in humidity and CF. The module temperature significantly influences module efficiency.

The forecast model derived can be used in management of distributed energy generation (DEG) system consisting of SPV systems. For most of the clear days, the model provides a minimal deviation (<15 %) from the measured values and for a few days with randomly changing weather or extreme weather conditions, it is as high as 18 %. This deviation is quite acceptable as it can be considered for maintaining other power sources as spinning reserve. The methodology used for deriving this model can be adopted at any location to forecast the power output from a SPV plant to tune the power generation from coal or natural gas fired power stations. This model is simple to use, especially for the consumer-end, mainly because it uses the forecast data available on the public domain. The accuracy of this model is dependent on the precision of forecast data available and weather conditions which are favourable for solar power generation.

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