Application of an $h$-adaptive finite element model for wind energy assessment in Nevada

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Abstract

A multiscale modeling project for wind energy assessment in central Nevada has been conducted. The PSU/NCAR fifth-generation Mesoscale Model (MM5) was used in conjunction with an $h$-adaptive finite element model and local tower data for a 1-year cycle for the central region. The MM5 results and the local tower data are used as input into the microscale $h$-adaptive FEM model. The $h$-adaptive module permits resolution down to meter levels, allowing more accurate details regarding topographic features and wind velocity vectors. Multiscale results for assessing wind energy potential are presented in the form of monthly averaged wind power density maps. Potential locations for establishing wind farms in the region are discussed.

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Keywords: Wind energy assessment; Multiscale modeling; $h$-adaptive finite element

1. Introduction

Wind energy still remains a limited resource in the Southwestern USA. Although the estimation of wind energy resources is rudimentary, a preliminary Wind Energy Atlas developed by NREL, MSOE and TrueWind Solutions [1] shows that Nevada has significant wind resource potential. However, there have been very little detailed wind energy resource data for Nevada, primarily due to inaccessibility to reach remote ridges and mountaintops where higher-class winds may exist; Class 3 or lower winds are common...
in most of the valleys. One of the main problems is the lack of appropriate wind data that have been accumulated over the years within Nevada.

The research reported in this effort stems partly from the collaboration of faculty and students within the Nevada Center for Advanced Computational Methods at the University of Nevada Las Vegas (UNLV), researchers at the Desert Research Institute (DRI) in Reno, and support from the Department of Energy (DOE) and National Renewable Energy Laboratory (NREL). In this research, multiscale modeling at both the mesoscale and microscale levels in wind energy assessment for central Nevada was conducted. The central region of Nevada was selected after a preliminary assessment based on climatological studies as to the best regions and highest wind power densities for potential wind farms in Nevada. The PSU/NCAR fifth-generation Mesoscale Model (MM5) was used to produce a series of simulations for a 1-year cycle in order to obtain preliminary wind data for the region. The MM5 mesoscale results were then used as input, along with meteorological data from the four towers, for the microscale \( h \)-adaptive FEM model.

The adaptive grid model can dynamically control grid size \( (h) \)—the grid refines and unrefines automatically based on the gradient and error distribution of topography and other key variables (such as velocity and wind power density). The \( h \)-adaptive finite element model is ideal for solving problems requiring large-scale calculations over regions where localized fine meshing is needed and yields far better accuracy than conventional, non-adapting numerical schemes. Coupled with meteorological tower data, accuracy in determining the best locations for wind turbine placement can be greatly improved. Spatial resolution can be refined from kilometers down to meter levels, permitting 3-D wind field estimation that accurately reflects topographic effects.

<table>
<thead>
<tr>
<th>Nomenclature</th>
</tr>
</thead>
<tbody>
<tr>
<td>( e ) computational error</td>
</tr>
<tr>
<td>( {f} ) load vectors</td>
</tr>
<tr>
<td>( (h) ) element size</td>
</tr>
<tr>
<td>( [K] ) diffusion matrix</td>
</tr>
<tr>
<td>( N_i ) shape function</td>
</tr>
<tr>
<td>( p ) shape function order</td>
</tr>
<tr>
<td>( t ) time</td>
</tr>
<tr>
<td>( u, v, w ) velocity components in ( x, y, z ) direction</td>
</tr>
<tr>
<td>( u_0, v_0, w_0 ) fixed observed velocity components in ( x, y, z ) direction</td>
</tr>
<tr>
<td>( V ) velocity vector</td>
</tr>
<tr>
<td>( W_i ) Petrov–Galerkin weighting function</td>
</tr>
<tr>
<td>( \Omega ) computational domain</td>
</tr>
<tr>
<td>( \eta ) error index</td>
</tr>
<tr>
<td>( \rho ) density</td>
</tr>
<tr>
<td>( z_i ) Gauss precision moduli</td>
</tr>
<tr>
<td>( \varepsilon ) convergence criteria</td>
</tr>
<tr>
<td>( \xi_i ) local element refine indicator</td>
</tr>
<tr>
<td>( \lambda ) Lagrange multiplier</td>
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</tbody>
</table>
A series of multiscale simulation results for assessing wind energy are presented in the form of monthly averaged wind power density maps. Potential locations for establishing wind farms in central Nevada are discussed. Regional and mesoscale modeling was performed using MM5, which has been used extensively since the late 1970s by many meteorologists. Detailed modeling descriptions in this paper are focused on the microscale adaptive finite element model.

2. Mass consistent FEM

The theoretical basis for the diagnostic, mass consistent FEM model stems from the early work of Sherman et al. [2] and later applied by Pepper [3]. The main idea of a mass consistent model is to minimize the differences between the observed velocity values and computed values. The goal is to attempt to match the simulation values with the measured meteorological data, using weighted averaging around the sparse data points to fill in values to all the nodes within the computational domain. It is especially important in simulating atmospheric flow. The main procedure for construction of this model is described as follows:

1. A surface wind field is constructed from measured data using inverse-squared weighting. A fixed radius is specified and value interpolated from measured tower data to all grid points in the first level above the terrain.
2. The upper level wind fields at all remaining grid points within the computational domain are constructed using inverse weighting from the surface-generated values.
3. Vertical velocities (if not measured) are calculated at all grid points from the equation of continuity
   \[ w = - \int_0^z \left( \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} \right) dz. \]  
   (1)
4. A global check of divergence is determined
   \[ \varepsilon = \int_\Omega \left( \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} \right) d\Omega. \]  
   (2)
5. An integral function that minimizes the variance of the difference between the observed and analyzed variables is evaluated. The specific function is
   \[ E(u, v, w, \lambda) = \int_\Omega \left[ \frac{\alpha_1^2 (u - u_0)^2 + \alpha_2^2 (v - v_0)^2}{\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z}} \right] d\Omega. \]  
   (3)

Euler–Lagrange equations for velocity readjustment are solved:
\[ u = u_0 + \frac{1}{2\alpha_1^2} \frac{\partial \lambda}{\partial x}, \]  
   (4)
\[ v = v_0 + \frac{1}{2\alpha_1^2} \frac{\partial \lambda}{\partial y}, \]  
   (5)
\[ w = w_0 + \frac{1}{2\alpha_2^2} \frac{\partial \lambda}{\partial z}. \]  
   (6)
where \(u, v, w\) are the adjusted velocity components in the \(x, y, z\) directions; \(u_0, v_0, w_0\) are the corresponding observed variables; \(\lambda(x, y, z)\) is the Lagrange multiplier, and the values of \(\alpha_i\) are Gauss precision moduli [2].

Substituting Eqs. (4)–(6) into the continuity equation, the resulting Poisson equation is then solved for the Lagrangian multiplier \(\lambda(x, y, z)\).

\[
\frac{\partial^2 \lambda}{\partial x^2} + \frac{\partial^2 \lambda}{\partial y^2} + \left( \frac{z_1}{x_2} \right)^2 \frac{\partial^2 \lambda}{\partial z^2} = -2x_1 \left( \frac{\partial u_0}{\partial x} + \frac{\partial v_0}{\partial y} + \frac{\partial w_0}{\partial z} \right). \tag{7}
\]

(6) Applying the Galerkin Weighted Residual technique, the matrix form of Eq. (7) becomes:

\[
[K][\lambda] = [f], \tag{8}
\]

where

\[
K = \int_\Omega \left[ \frac{\partial N_i}{\partial x} \frac{\partial N_j}{\partial x} + \frac{\partial N_i}{\partial y} \frac{\partial N_j}{\partial y} + \frac{z_1^2}{x_2^2} \frac{\partial N_i}{\partial z} \frac{\partial N_j}{\partial z} \right] \, d\Omega \tag{9}
\]

and

\[
f = 2x_1 \int_\Omega N_i \left( \frac{\partial u_0}{\partial x} + \frac{\partial v_0}{\partial y} + \frac{\partial w_0}{\partial z} \right) \, d\Omega. \tag{10}
\]

(7) Once \(\lambda(x, y, z)\) is calculated, the velocity components are adjusted according to Eqs. (4)–(6).

(8) Return to step 4 until convergence, normally using \(\varepsilon \approx 10^{-4}\).

Both the Lagrangian multiplier \(\lambda(x, y, z)\) and the normal velocity component variation are zero on a boundary. Generally, when \(\lambda(x, y, z) = 0\) on a boundary, the normal derivative of \(\lambda(x, y, z)\) is not zero. An adjustment of the velocities results from using Eqs. (4)–(6). A non-zero adjustment of the velocity component normal to the boundary implies a change in the amount of mass entering or leaving the volume. Therefore, the boundary condition \(\lambda = 0\) is appropriate for open or "flow-through" boundaries. A constant value for \(\lambda(x, y, z)\) on an open boundary also implies no adjustment is made in the non-normal velocity components, since the non-normal derivatives of \(\lambda(x, y, z)\) are zero.

If the variation of the normal velocity component is zero on the boundary, the adjusted value of the normal velocity must be the observed value. From Eqs. (4) to (6), it is apparent that setting the normal derivative of \(\lambda(x, y, z)\) equal to zero on the boundary specifies no variation of the normal velocity component at that boundary. If the observed normal velocity is zero, this boundary condition implies no transport of mass across the boundary. Therefore, the condition \(\partial \lambda / \partial n = 0\) is used for closed or "no-flow-through" boundaries.

In this study, the initial wind field is obtained by interpolating MM5 output coupled with meteorological data. The diagnostic procedure produces a mass consistent, realistic, and fairly accurate 3-D wind field, which can then be refined to account for microscale topographic features.
3. Adaptive methodology

Generally, there are four main categories of adaptation: \textit{h}-adaptation, where the element size varies while the order of shape function remains constant; \textit{p}-adaptation, where the element size is constant while the order of the shape function is increased to meet the desired accuracy requirement; \textit{r}-adaptation, where spring analogy redistributes the nodes in an existing mesh; and \textit{hp}-adaptation, which is the combination of both \textit{h}-and \textit{p}-adaptation. The comparison of the four adaptive methods is shown in Table 1.

The use of mesh adaptation is one of the more powerful tools now being used in many numerical simulations. The \textit{h}-adaptive FEM is especially promising in atmospheric simulation, which typically requires large-scale calculations over regions where localized fine meshing is needed to capture fast change flow features. Peraire et al. [4] were among the first to successfully use \textit{h}-adaptive FEM techniques to accurately capture shock waves in compressible flows. Today, adaptive techniques have been adopted in many commercial CFD codes and used by many researchers over a wide range of applications [5–9]. However, application of such techniques to atmospheric models has been very limited [10,11], even though there has been numerous adaptive models developed over many years [4–11].

\textit{h}-adaptation itself is not complex, but specific adaptation rules must be followed. In \textit{h}-adaptation, one of the most important rules is the 1-irregular mesh rule, which states that: an element can be refined only if its neighbors are at the same or higher level (1-irregular mesh). By following this rule, multiple constrained nodes (parent nodes themselves are constraint nodes) can be avoided.

2-D \textit{h}-adaptation examples are given in Figs. 1(a–c). In Fig. 1(a), among the four smaller elements only element 1 can be refined at this time, as shown in Fig. 1(b). Element 4 cannot be refined since it has neighbor elements with a lower adaptation level. Fig. 1(c) shows an incorrect adaptive mesh for element 4, which violates the 1-irregular mesh rule.

3-D \textit{h}-adaptation examples are given in Figs. 2(a–c). In Fig. 2(a), among the eight smaller elements only element 1 can be refined at this time, as shown in Fig. 2(b). Element 4 cannot be refined since it has neighbor elements with a lower adaptation level. Fig. 2(c)

<table>
<thead>
<tr>
<th></th>
<th>\textit{h}-adaptation</th>
<th>\textit{p}-adaptation</th>
<th>\textit{r}-adaptation</th>
<th>\textit{hp}-adaptation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Element size</td>
<td>Various</td>
<td>Constant</td>
<td>Various</td>
<td>Various</td>
</tr>
<tr>
<td>DOF (degrees of freedom)</td>
<td>Various</td>
<td>Various</td>
<td>Constant</td>
<td>Various</td>
</tr>
<tr>
<td>Shape function</td>
<td>Constant</td>
<td>Various</td>
<td>Constant</td>
<td>Various</td>
</tr>
<tr>
<td>Advantages</td>
<td>Elements will not become overly distorted</td>
<td>Relative coarse mesh may be sufficient</td>
<td>No new nodes need to be added</td>
<td>Exponential convergence rate</td>
</tr>
<tr>
<td>Disadvantages</td>
<td>Difficulty in dealing with constraint nodes</td>
<td>Coding complexity</td>
<td>Elements may become overly distorted</td>
<td>Difficulty in dealing with constraint nodes and coding complexity</td>
</tr>
</tbody>
</table>
shows an incorrect adaptive mesh for element 4, which violates the 1-irregular mesh adaptation rule.

3.1. Error estimator

Two factors must be carefully considered to conduct a successful $h$-adaptive FEM process: the error estimator and the adaptation strategy. A well-chosen error estimator is very important in any adaptation process: a poor error estimator results in incorrect refine or unrefined with too many generated elements in smooth flow regions or too coarse meshes in fast change flow regions. A good error estimator in practical usage does not necessarily have to be the most accurate, and could become prohibitively expensive if refinement is set to be too restrictive. A better error estimator is one that is reasonably accurate and relatively easy to compute.

Many error estimators for $h$-adaptation exist in the literature, such as gradient-based error estimators, curvature-based error estimators, or energy norm-based error estimators. Detailed descriptions of these error estimators can be found in [12,13]. In this study, an error estimator was chosen based on an extension of the work by Zienkiewicz and Zhu [14], which yields reasonable accuracy, is simple, and easy to implement.

The basis for this error estimator stems from the error norm for linear elasticity. The error in a finite element solution is the difference between the exact and approximate solutions, i.e., the error in displacement,

$$e_u = u - u_h,$$

Likewise, the error for the stresses can be expressed as

$$e_\sigma = \sigma - \sigma_h,$$

where $u_h$ and $\sigma_h$ indicate the finite element solutions, while $u$ and $\sigma$ indicate the exact solutions. In most practical problems, exact solutions are usually unavailable—however, a
continuous solution obtained by a projection or averaging process can be substituted, i.e., 
\[ u^* - u_h \quad \text{and} \quad \sigma^* - \sigma_h. \] (13)

The "\(L_2\)" norm error estimator is adopted in this study and the corresponding stress 
error measure can be expressed as
\[ ||e_\sigma|| = \left( \int_{\Omega} e_\sigma^T e_\sigma \, d\Omega \right)^{1/2}, \] (14)
where all element errors are typically defined as
\[ ||e_\sigma||^2 = \sum_{i=1}^{m} ||e_\sigma||_i^2, \] (15)
where \(m\) stands for the total number of elements.

We can now define the error index \(\eta = \eta_\sigma\) in the form of error percentage as
\[ \eta_\sigma = \left( \frac{||e_\sigma||^2}{||\sigma^*||^2 + ||e_\sigma||^2} \right)^{1/2} \times 100\%. \] (16)

The error index \(\eta\) is used to guide the adaptation procedure. The total velocity is chosen 
as the key adaptation variable in this study.

3.2. Adaptation strategy

An acceptable solution is reached when global and local error conditions are met [15]. A 
global error condition states that the global percentage error should not be greater than 
a maximum specified percentage error: \(\eta \leq \tilde{\eta}_{\max}\). If \(\eta > \tilde{\eta}_{\max}\), a new iteration is performed. The 
local error condition states that local relative percentage error of any single element 
\(||e_\sigma||_i\) should not be greater than the averaged error \(\tilde{e}_{\text{avg}}\) among all the elements in the 
domain. The average element error is defined as
\[ \tilde{e}_{\text{avg}} = \tilde{\eta}_{\max} \left[ \frac{\left( ||\sigma^*||^2 + ||e_\sigma||^2 \right)}{m} \right]^{1/2}. \] (17)

A local element refinement indicator is defined to decide if a local refinement for an 
element is needed, i.e.
\[ \xi_i = \frac{||e||_i}{\tilde{e}_{\text{avg}}}, \] (18)
when \(\xi_i > 1\), the element is refined; when \(\xi_i < 1\) the element is unrefined. In an \(h\)-adaptive 
process, the new element size is calculated using
\[ h_{\text{new}} = \frac{h_{\text{old}}}{\xi_i^{1/p}}. \] (19)
4. Simulation results

Early assessment studies implied little potential for wind energy within Nevada. However, recent assessments now suggest the contrary, with many more ridge sites as possible candidates for wind farms. Data from previous wind assessment studies conducted for Nevada were first published in 1986 [16]. Recent efforts since 2003 have drastically revised these previous studies—see Fig. 3 [17]. However, even the recent studies are not complete, and only several viable sites have been examined over any length of time, e.g., yearlong meteorological data using local towers. Truewind developed wind energy maps for various regions of the USA, including Nevada. These assessment studies are preliminary, do not include on-site meteorological tower data, and are based on relatively coarse mesh spacing (~1–2 km). By employing multiscale modeling, high-resolution wind power density maps can be constructed for selected domains in Nevada.

Fig. 3. Wind energy resource map—2003 study (TrueWind Solutions [17]).
4.1. Computational mesh

Initial setup of the mesoscale MM5 modeling domain is shown in Fig. 4 (grid dimensions are $120 \times 95 \times 39$ for domain 1 and $118 \times 85 \times 39$ for domain 2). The horizontal resolution is 9 km for domain 1 and 3 km for domain 2, 39 full sigma levels are used in the vertical direction.

Mesoscale simulation was conducted using NCAR data for an entire year—starting from September 1st, 2001 to August 31st, 2002. Four 50 m towers were installed at locations, which indicated preliminary high-potential wind power density profiles. The four site locations are listed in Table 2.

The microscale, $h$-adaptive FEM model was then used to increase computational resolution and determine the optimal location for sitting wind turbines. The FEM domain included the 4 tower locations ranging from 116.9° to 118.4° west longitude to 38.3°–39.1° north latitude. A terrain following computational mesh for the FEM was generated from Digital Elevation Map (DEM) data, developed by the USGS. The DEM location is shown in Fig. 5 corresponding to the computational domain. Fig. 6 shows the terrain surface plot (a) and topographic contours (b)—the units for the elevation are in meters.

The initial mesh consisted of 5 coarse vertical levels set at: (1) surface level, (2) 50 m level, (3) 100 m level, (4) 300 m level and (5) 1500 m level. Horizontal resolution was set to 3 km for the initial mesh. Both 3-D and 2-D views of the initial computational mesh are shown in Fig. 7(a) and (b)—the non-orthogonal, unstructured meshes are shown with tower locations as grid points, which are indicated as dots. The entire mesh consisted of 4872 elements and 6450 nodes.
4.2. Wind power density calculation

Nevada’s electricity potential from wind energy is estimated to be approximately 5769 MW [18]. The wind potential accounts for about 0.6% of the total US consumption—in terms of fossil-fuel displacement equivalency [19].

Table 2
Four-tower site locations

<table>
<thead>
<tr>
<th>Site no.</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Elevation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Deg Min Sec</td>
<td>Deg Min Sec</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>39 05 52.97</td>
<td>117 03 47.36</td>
<td>1674</td>
</tr>
<tr>
<td>2</td>
<td>38 22 19.42</td>
<td>117 28 17.74</td>
<td>1540</td>
</tr>
<tr>
<td>3</td>
<td>38 34 20.99</td>
<td>118 10 31.68</td>
<td>1520</td>
</tr>
<tr>
<td>4</td>
<td>38 32 37.39</td>
<td>118 17 39.91</td>
<td>1354</td>
</tr>
</tbody>
</table>

Fig. 5. DEM location of the computational domain.

Fig. 6. Initial computational mesh. (a) 3-D view and (b) 2-D view (dots denote tower locations).
Wind power density is classified into seven categories, ranging from Class 1 (lowest) to Class 7 (highest), as shown in Table 3. This classification uses a vertical extrapolation of wind speed based on the 1/7 power law. Mean wind speed is based on the Rayleigh speed distribution of equivalent wind power density. Wind speed is for standard sea-level conditions. The source of this classification data is from the Battelle Wind Energy Resource Atlas [20]. Generally, Class 4 winds and higher are considered to be satisfactory for power generation, although Class 3 winds are becoming potentially viable as new wind turbine technology evolves.

In this study, the wind power density calculations are summarized in the following steps:

1. Calculate the wind speed at each grid point on an hourly basis

   \[ \text{Speed}_i = \sqrt{u_i^2 + v_i^2 + w_i^2}. \]  

2. Calculate the hourly wind power density at each grid point. The basics for wind energy calculation come from the relations of kinetic energy (\(mV^2/2\)) and momentum (\(mV\)). For an average Standard Temperature and Pressure (STP) atmosphere, the wind power density can be calculated using

   \[ \text{WPD}_i = 0.5\rho \text{Speed}_i^3, \]  

   where the unit for wind power is W, the unit for area is \(m^2\), the unit for wind velocity is \(m/s\), and the density for air is 1.225 \(kg/m^3\) at sea level. The density for air at elevation \(Z\) (\(Z\) is the location’s elevation above sea level, with unit m) is obtained using

   \[ \rho = 1.225 - (1.194 \times 10^{-4}) \times Z. \]  

3. The monthly average wind power density is calculated using

   \[ \text{WPD}_{\text{monthly, avg}} = \frac{\sum_{i=1}^{N} \text{WPD}_i}{N}, \]  

   where \(N\) is the total number of hours in a selected month.
Table 3
Wind power density classification [20]

<table>
<thead>
<tr>
<th>Wind power class</th>
<th>50 m</th>
<th>Wind power density (W/m²)</th>
<th>Mean speed range (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;200</td>
<td>&lt;5.6</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>200–300</td>
<td>5.6–6.4</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>300–400</td>
<td>6.4–7.0</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>400–500</td>
<td>7.0–7.5</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>500–600</td>
<td>7.5–8.0</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>600–700</td>
<td>5.6–8.8</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>&gt;800</td>
<td>&gt;8.8</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 8. (a) 50 m WPD classes and (b) 100 m WPD (W/m²) (September 2001).

Fig. 9. (a) 50 m WPD classes and (b) 100 m WPD (W/m²) (October 2001).
4.3. Monthly averaged wind power density

Monthly wind power density maps were generated for the simulation period from September 1st, 2001 to August 31st, 2002 using Eqs. (20)–(23). Figs. 8–19 show (a) 2-D views of the average wind power density classes, together with the black terrain height contour lines for a height level of 50 m and, (b) 2-D views of the average wind power densities for a height above terrain of 100 m. The units for wind power densities are W/m². (The dots denote the pre-selected horizontal locations for the four towers.)

4.4. Adaptive simulation results

Following a review of the 1-year simulation results, December 2001 was chosen to test the adaptive FEM mass consistent model. The reasons for selecting December are: (1) December has the highest peak value of the whole year cycle and, (2) the month represents the most optimal wind power density distribution pattern in the year.

![Figure 10](image1.png)

Fig. 10. (a) 50 m WPD classes and (b) 100 m WPD (W/m²) (November 2001).

![Figure 11](image2.png)

Fig. 11. (a) 50 m WPD classes and (b) 100 m WPD (W/m²) (December 2001).
Fig. 12. (a) 50 m WPD classes and (b) 100 m WPD (W/m²) (January 2002).

Fig. 13. (a) 50 m WPD classes and (b) 100 m WPD (W/m²) (February 2002).

Fig. 14. (a) 50 m WPD classes and (b) 100 m WPD (W/m²) (March 2002).
Fig. 15. (a) 50 m WPD classes and (b) 100 m WPD (W/m$^2$) (April 2002).

Fig. 16. (a) 50 m WPD classes and (b) 100 m WPD (W/m$^2$) (May 2002).

Fig. 17. (a) 50 m WPD classes and (b) 100 m WPD (W/m$^2$) (June 2002).
A 4-level $h$-adaptive procedure was employed. The final adaptive mesh consisted of 45,136 elements and 59,482 nodes. Fig. 20 shows the corresponding 100-m height level wind power densities map for December, 2001 data.

The mesh refinement parameters were based on velocity gradients and topography. Notice the refined mesh with increased topography, which similarly corresponds to increased wind velocities flowing over ridges and peaks. Compared with results shown in Fig. 11 (where the horizontal resolution is 3 km), the highest wind power density locations become much easier to identify (in this instance, the horizontal resolution refined to 275 m). Further refinement was not deemed necessary. In this instance, the meteorological towers should be relocated to measure velocities where either more sustained or higher classes of winds occur.

5. Conclusion

A multiscale modeling approach has been applied for wind energy assessment for central Nevada. MM5 mesoscale model output and available field measurements are used to
provide initial input data for the microscale adaptive FEM model. Results from MM5 provide reasonable and accurate estimates of winds at regional/mesoscale levels. At the microscale level, the $h$-adaptive model permits the construction of high-resolution wind power densities, which can be used to refine meteorological tower locations and potential wind turbine sites. The $h$-adaptive FEM algorithm refines and unrefines meshes automatically based on velocity and/or topographical gradients. This has been found to be especially advantageous when dealing with large-scale calculations over regions where localized fine meshing is needed to capture rapidly changing flow features. The adaptive finite element model can be used to provide more accurate guidance to a wind farm developer in choosing the best site and optimal distribution of wind turbines.

Monthly averaged wind power densities map were constructed for a 1-year cycle for central Nevada. Results show that wind power densities for the selected computational domain are mainly in power classes 2-4. An adapted high-resolution wind power density map was constructed for December 2001, which had the highest peak values and potential wind power densities pattern over the entire year. Identification of optimal wind power density locations can be more easily conducted by examining the adaptive results. Simulation results also indicated that the pre-selected 4 tower locations were not positioned at optimal high wind locations and needed to be shifted. Additional studies are underway for other regions of Nevada, especially in those regions within the state where Class 3–4 regions may be fruitful.
Acknowledgements

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References